Advancements in Weed Mapping and Herbicide Spraying: A Comprehensive Review of UAV Technologies and Applications

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Abstract *Weed management is a crucial factor in agricultural production, traditionally reliant on labor-intensive and chemical-heavy methods. The advent of unmanned Aerial Vehicles offers a transformative approach to this challenge, providing precise weed mapping and targeted herbicide spraying. This review paper explores the comprehensive role of unmanned aerial vehicles in weed management, detailing the types of drones used, such as multi-rotor, fixed-wing, and hybrid drones, and the sensors and cameras they employ for high-accuracy weed detection and mapping. We delve into the major unmanned aerial vehicles models used for both weed mapping and herbicide dispersion and compare the efficiency and environmental impact of unmanned aerial vehicle technology with conventional methods. Various herbicides dispersed via unmanned aerial vehicles are discussed, along with their classification based on climate and edaphic factors. The efficiency and persistence of herbicides applied using drones are evaluated against traditional spraying methods. The integration of deep learning techniques in unmanned aerial vehicle-based weed mapping is a significant advancement, enabling the analysis of complex datasets through architectures like convolutional neural networks. This review examines the datasets, training techniques, data augmentation strategies, and performance metrics crucial for enhancing weed detection accuracy. Our review indicates that unmanned aerial vehicles offer a highly efficient, precise, and environmentally friendly alternative to conventional weed management practices. This paper provides a detailed comparison of unmanned aerial vehicle herbicide sprayers with traditional sprayers, underscoring the potential unmanned aerial vehicle technology to revolutionize weed management and improve agricultural sustainability.*

Keywords: Convolutional neural networks, deep learning, herbicide spraying, unmanned aerial vehicle, weed mapping.

Introduction [

Weed management is a decisive component of cutting-edge agriculture, essential for ensuring crop health and maximizing yields. Ancestral methods of weed detection and herbicide application often involve significant labour, time, and environmental impact due to the widespread use of chemicals. UAVs have emerged as a transformative technology in this field, offering precise, efficient, and environmentally friendly solutions for weed mapping and herbicide spraying. UAVs, commonly known as drones, are increasingly being utilized in agricultural practices due to their ability to cover large areas quickly and collect high-resolution data. These UAVs can be equipped with a variety of sensors and cameras that facilitate the detection and mapping of weeds with high accuracy. This technology allows for the targeted application of herbicides, reducing the overall amount of chemicals used and minimizing their impact on the environment (Huang et al., 2018). The types of UAVs used in weed management vary in terms of size, capability, and the type of sensors they carry. Multi-rotor drones, fixed-wing drones, and hybrid drones each offer distinct advantages and limitations depending on the specific application (Zhang & Kovacs, 2012). Multi-rotor drones are highly maneuverable and suitable for small areas or fields with complex terrain, while fixed-wing drones can cover larger areas more efficiently. Hybrid drones combine the benefits of both types, offering extended flight times and enhanced manoeuvrability. Sensors such as multispectral, hyperspectral, and RGB cameras play a crucial role in weed detection by capturing detailed images that can be analyzed using advanced algorithms. Multispectral sensors capture data in specific wavelength bands, providing information about plant health and stress. Hyperspectral sensors collect data across a wide range of wavelengths, allowing for detailed analysis of plant characteristics and better discrimination between crop and weed species. RGB cameras, though less sophisticated, are cost-effective and useful for general weed mapping tasks (Torres-Sánchez et al., 2015). The integration of advanced imaging techniques with UAV technology has significantly enhanced the capability of weed detection. These techniques involve the use of image processing algorithms to analyze the captured data and identify weed species. Machine learning and deep learning algorithms, in particular, have shown great promise in improving the accuracy and efficiency of weed detection (Lottes et al., 2017). Deep learning techniques, such as convolutional neural networks (CNNs), allow for the analysis of complex datasets and the development of robust models for weed detection. These models can learn to recognize weed patterns from large datasets, improving over time as more data is collected. This capability is crucial for creating accurate weed maps, which can be used to guide targeted herbicide application (Kamilaris & Prenafeta-Boldú, 2018). UAVs equipped with precision spraying systems can apply herbicides directly to identified weed patches, reducing the overall amount of chemicals used and minimizing their impact on the environment. This targeted approach is not only more efficient but also more cost-effective compared to conventional blanket spraying methods (Zhang et al., 2020). UAVs can operate in a variety of climatic and edaphic conditions, offering flexibility that traditional methods lack (Jiang et al., 2019). Different herbicides can be dispersed using UAVs, and their effectiveness can vary based on climate and soil factors. Studies have shown that UAV-based herbicide application can achieve comparable or even superior results to conventional methods in terms of weed control and crop yield (Zhang et al., 2020). The persistence of herbicides applied via UAVs has also been a subject of study, with findings indicating that UAV applications can lead to more uniform coverage and better penetration in dense crop canopies (Zhao et al., 2019). Comparing UAV technology with conventional weed management methods reveals several benefits. UAVs provide precise and targeted herbicide application, which can lead to cost savings and reduced environmental impact. Additionally, UAVs can operate in a variety of climatic and edaphic conditions, offering flexibility that traditional methods lack. UAVs also reduce the need for manual labor and can cover large areas quickly, making them an attractive option for large-scale farming operations (Raja et al., 2020). Deep learning techniques have further enhanced the capability of UAVs in weed mapping. These techniques allow for the analysis of complex datasets and the development of robust models for weed detection. Convolutional Neural Networks (CNNs) and other deep learning architectures can analyze high-resolution images captured by UAVs to identify and classify weed species with high accuracy. The use of large, annotated datasets and advanced training techniques has been crucial in developing these models (Sa et al., 2018). Data augmentation techniques, such as rotating, flipping, and scaling images, are used to increase the diversity of training data and improve the robustness of deep learning models. Performance metrics, such as precision, recall, and F1 score, are used to evaluate the accuracy of these models and their effectiveness in real-world scenarios (Milioto et al., 2019). This review paper provides a comprehensive overview of the advancements in UAV technology for weed mapping and herbicide spraying. It covers the types of UAVs and sensors used, the efficiency and persistence of herbicides applied via UAVs, and the application of deep learning in weed detection. Furthermore, it compares UAV-based methods with conventional technologies, highlighting the potential of UAVs to revolutionize weed management practices.

2. UAV in Weed mapping.

Drones are being used for weed mapping in precision agriculture (Gunasekaran and Raja.,2023). Cameras mounted on Unmanned Aerial Vehicles (UAVs) are employed to photograph agricultural fields, and machine learning algorithms are then used to identify and classify weeds (Ran and Meng ., 2023).Various measurements, including spectral, textural, structural, and thermal, are integrated to enhance the precision of weed identification (Mahmoud, 2023).The combination of textural, structural, and thermal characteristics has proven to be most effective in mapping weeds. Moreover, the application of deep neural networks along with unscented Kalman filter estimation methods has been suggested for the automatic detection and localization of weeds using drone imagery. These technological improvements in drones and analytical methods are vital for quick and efficient weed identification, crucial in managing weed growth and supporting crop yield within the framework of precision agriculture. UAVs can quickly cover large areas of land, capturing photographic images to identify patches of weeds (H. Li, 2019). And these images are processed using deep neural networks (DNN), convolutional neural networks, and object-based image analysis (OBIA) techniques. A technique that uses color analysis to identify green weeds, such as Cirsium arvense, in cereal crops prior to harvesting has been adopted. RGB cameras mounted with UAV have successfully identified 92-97% of the areas where C. *arvense* was the predominant weed under different environmental conditions (J. Rasmussen and J. Nielsen., 2019). Improving weed identification accuracy in an MD4-1000 quadcopter model requires pinpointing the exact location of each plant in the crop row formation. The method for creating weed maps operates autonomously in three steps: 1) classifying crop rows, 2) distinguishing between crop plants and weeds using their respective locations, and 3) creating a map of weed presence using a grid system. This approach aids in minimizing the use of herbicides by adjusting the amount applied based on the level of weed invasion observed (J.M. Pen˜a, 2013). The UAV eBee, fitted with GPS, collects multispectral images to identify infestations of weeds like lamb's quarters (Chenopodium album) and thistle (Cirsium arvense) within maize crops. This study highlights the significance of spatial resolution in identifying weeds of specific sizes, an essential factor for advancing UAV-based technology for weed detection (M. Louargant and S. Villette., 2017). One notable study by Torres-Sánchez et al. (2015) utilized drones equipped with multispectral sensors for weed detection and mapping in agricultural fields. The authors demonstrated the potential of drones to accurately identify and map different weed species, highlighting their efficacy in precision agriculture applications.

Similarly, the research conducted by Qin et al. (2016) employed unmanned aerial vehicles (UAVs) to monitor and map weed distribution in maize fields. The study demonstrated the capability of drones to capture detailed spatial information of weed infestations, aiding in targeted weed management strategies. Furthermore, the work of Calle et al. (2019) focused on using drones for weed mapping in vineyards. By employing aerial imagery captured by UAVs, the researchers successfully identified and mapped weed species within vineyard plots, showcasing the utility of drones for site-specific weed management. the use of UAVs to detect stress in tomatoes caused by herbicide drift. The UAV equipped with sensors detected subtle differences in plant stress induced by herbicide application, demonstrating the potential for targeted herbicide spraying (Zhang, M.,2018). the use of small UAVs for precision agriculture, including their application in herbicide spraying. It discusses the benefits and challenges of using UAVs for herbicide application and highlights their potential for improving efficiency and reducing herbicide use. (Bates, T.,2018). UAV-based aerial imagery for early detection of weed competition in maize fields. It demonstrates the potential of UAVs to detect weeds early in the growing season, allowing for timely herbicide application to mitigate weed competition. (Marchi, M.,2019).

2.1 Types of UAV used in Weed management for Weed detection and Herbicide spraying.

The application of UAVs for herbicide spraying involves the evaluation of spray volume, droplet size, and deposition to optimize the control of pests and diseases in crops (Wang et al., 2019). Additionally, the use of UAVs for early weed detection and mapping facilitates the generation of site-specific weed treatments, reducing the overall use of herbicides while enhancing their chemical effects (Huang et al., 2018). Images were gathered at an altitude of 30 meters using a DJI Phantom 4 Pro quadcopter (DJI), with mission planning conducted via the Pix4D Capture application on an iPad mini 4 (Apple, Cupertino, CA, USA). These images were then stitched together using Agisoft PhotoScan 1.4.4 software (Agisoft, LLC, St Petersburg, Russia) to produce an orthophoto with a spatial resolution of 0.82 cm per pixel for the entire experimental field. Ground landmarks were utilized to validate coordinates (Hunter, J.E., 2020). LiDAR-equipped UAVs employ laser scanning technology to generate detailed 3D models of terrain and vegetation. These models enable accurate detection and mapping of weeds (Anderson et al., 2018). A technique that utilizes color analysis to identify green weeds, specifically Cirsium arvense, in cereal crops prior to harvesting has been put into practice. In different environmental conditions, RGB cameras were able to accurately classify between

92% and 97% of the areas where C. arvense was prevalent (J. Rasmussen et.al 2019). Compact consumer drones, such as the Phantom 3 or 4, have the ability to map 10 hectares in 20 minutes while flying at a height of 40 meters. In a particular vineyard, a quadcopter drone was used to take aerial RGB (red-green-blue) photographs for the purpose of mapping weed patches. This enabled the optimization of targeted weed management while C. dactylon was in its dormant phase, using an Object-Based Image Analysis (OBIA) strategy for the early identification and mapping of these areas (A.I. de Castro et al. 2017). Fixed-wing UAVs offer long flight endurance and are suitable for large-scale weed detection. They can carry different types of sensors, such as multispectral or hyperspectral cameras, to identify weeds. (Torres-Sánchez et al., 2018). Thermal cameras mounted on UAVs can detect temperature differences between weeds and crops, making them useful for weed identification, especially in early stages of growth. (Khan et al., 2020). Helicopter-style UAVs offer a balance between multirotors and fixed-wing UAVs. They can handle larger payloads and are often used for herbicide spraying in vineyards and orchards (Yang, P., Zhou, Q., & Zhang, F. 2013). The MD4-1000 quadcopter UAV, equipped with GPS and either an RGB or multispectral camera, is used to identify and map weeds, crop rows, and bare soil. This process is carried out using a suitable and automated object-based image analysis (OBIA) framework, which helps in generating precise maps for site-specific herbicide application (F. Lo´pez-Granados *et al*. 2016). The UAV eBee, outfitted with GPS technology, is capable of taking multispectral photographs to identify weed infestations, specifically lamb's quarters (Chenopodium album) and thistle (Cirsium arvense), within maize crops. This research highlights two dicotyledonous weeds and emphasizes the crucial role of spatial resolution for recognizing various weed sizes, an essential factor in advancing drone-based weed detection methods (M. Louargant et al. 2017). The analysis of images of weeds makes use of advanced machine learning techniques, including DNN, CNN, and OBIA methods. A thorough review of studies on identifying weeds using unmanned aerial vehicles (UAVs) identifies three main types of imaging technologies: RGB (standard color imaging), multispectral, and hyperspectral cameras.(. (W.H. Maes., 2019 and D.C. Tsouros., 2019).

Table 1: Types of drones

Drone Type	Advantages	Disdavantages	Uses/Price
Multi rotor	• High accessibility • User-friendly • Vertical Takeoff and Landing (VTOL) and hover capability • Excellent camera control • Capable of operating in confined spaces	• Limited flight duration • Low payload capacity	• Aerial photography and videography • Aerial inspections • Price: $5,000 - $65,000 for professional models
Fixed wing	• Long flight endurance • Large area coverage • High-speed flight	• Requires ample space for launch and recovery • No VTOL/hover capability • More complex to operate, requiring additional training • High cost	• Aerial mapping • Pipeline and power line inspections • Price: $25,000 - $120,000 for professional models
Single rotor	• VTOL and hover capability • Longer endurance with gas-powered options • Greater payload capacity	• Increased danger • More difficult to operate, necessitating more training • Expensive	• Aerial LIDAR laser scanning • Price: $25,000 - $300,000 for professional model
Fixed wing hybrid	• VTOL capability • Extended flight endurance	• Not optimized for either hovering or forward flight • Still under development	• Drone Delivery • Price: TBD, under development

Multi-rotor drones are popular for their ease of use, VTOL capability, and ability to hover, making them ideal for aerial photography and inspections. However, they have limited flight time and payload capacity, with prices ranging from $5,000 to $65,000. Fixed-wing drones offer longer flight endurance and cover larger areas but require space for launch and lack hover capabilities, costing $25,000 to $120,000. Single-rotor drones have better endurance and payload capacity but are more dangerous and expensive, typically used for LIDAR scanning. Fixed-wing hybrid drones combine VTOL and long endurance but are still under development.

Table 2: Sensors/cameras used to map the weeds for site specific herbicide spraying

Sensor Type	**Principle of Operation**	**Examples of Weeds Detected**	**Citation**
RGB Cameras	Captures red, green, and blue light images	Dandelion (Taraxacum spp.), Chickweed (Stellaria media), Crabgrass (Digitaria spp.), Nutsedge (Cyperus spp.)	Nguyen et al., 2020
Multispectral Sensors	Captures data at specific wavelength bands	Pigweed (Amaranthus spp.), Lambsquarters (Chenopodium album), Wild Mustard (Sinapis arvensis), Bindweed (Convolvulus arvensis)	Ge et al., 2019
Hyperspectral Sensors	Captures a wide spectrum of light data	Johnsongrass (Sorghum halepense), Canada Thistle (Cirsium arvense), Wild Radish (Raphanus raphanistrum), Foxtail (Setaria spp.)	Khan et al., 2018
LiDAR	Uses laser pulses to measure distances	Bushes and woody weeds, Giant Ragweed (Ambrosia trifida), Tree-of-heaven (Ailanthus altissima), Russian Olive (Elaeagnus angustifolia)	Tilly et al., 2014
Thermal Cameras	Captures heat emissions	Nightshade (Solanum spp.), Ragweed (Ambrosia artemisiifolia), Velvetleaf (Abutilon theophrasti), Johnson Grass (Sorghum halepense)	Rasmussen et al., 2019

Figure 1: Types of UAVs/drones for mapping weeds

(a) Multi rotor (b) Fixed wing (c) Single rotor (d) Fixed wing hybrid

Figure 2: Sensors/Cameras equipped with UAVs for weed mapping

(a) RGB Camera (b) Multispectral Sensor (c) Hyperspectral Camera (e) Thermal Camera (d) LiDAR Sensor

3. Comparison of Unmanned Ariel Vehicle technology and conventional technology in weed management

3.1 Weed detection and herbicide spraying

UAV technology has demonstrated superiority in weed detection compared to conventional technology. Remote imagery obtained from UAVs holds notable promise for developing precise, site-specific weed management strategies during early post-emergence, capabilities that were previously unattainable with conventional airborne or satellite images (Peña et al., 2013). UAVs can capture high spatial resolution imagery, providing more detailed information for weed mapping compared to satellite and piloted aircraft remote sensing (Huang et al., 2018). Research indicates that UAV hyperspectral imaging techniques have become an invaluable tool in agricultural remote sensing, offering significant potential for weed detection and species differentiation (Sulaiman et al., 2022). Additionally, the integration of UAV technology with machine learning techniques has been found to be efficient and practical for detecting weeds from UAV images (Islam et al., 2021). Furthermore, the use of UAVs has been proposed for performing spraying, graded as safer and more precise compared to traditional methods (Khan et al., 2021). In contrast, conventional technology such as ground-based robots equipped with RGB cameras have been utilized for automated weed removal, employing either targeted herbicide spraying or mechanical in-row elimination (Dobbs et al., 2022). Additionally, LiDAR technology has been explored for ground weed detection in agricultural fields (Peteinatos et al., 2013). However, the potential of ground-based sensor technologies for weed detection is limited to detecting growing plants, with little opportunity for further development to discriminate between crop and weed plants (Coleman et al., 2021). UAV technology has shown significant advantages over conventional technology in weed detection. Studies have demonstrated that UAVs can capture high spatial resolution imagery, providing more detailed information for weed mapping compared to conventional methods (Huang et al., 2018). The efficacy and limitations of UAV technology for early detection of weed seedlings have been quantified, highlighting the potential of UAVs in this application (Peña et al., 2015). And the application of hyperspectral remote sensing imagery (HRSI) from UAVs has emerged as a valuable tool for weed detection, showing tremendous promise in agricultural remote sensing (Sulaiman et al., 2022). Moreover, an efficient weed detection procedure using low-cost UAV imagery systems for precision agriculture applications has been proposed, further emphasizing the potential of UAV technology in weed management (Hassanein & El-Sheimy, 2018). Drones fitted with different sensors (e.g., multispectral, hyperspectral, and LiDAR) can capture high-resolution imagery of large agricultural areas quickly and efficiently (Hunt et al., 2019). Conventional methods, such as manual scouting or satellite imagery, are time-consuming and may not provide sufficient spatial resolution for accurate weed detection (Oakes et al., 2017). UAVs can fly at low altitudes, providing high spatial resolution data, which is crucial for precise weed identification (Peña et al., 2015). Conventional methods may miss small patches of weeds or lack the spatial detail needed for effective management (Andújar et al., 2013). UAVs allow for real-time data acquisition and processing, enabling immediate weed management decisions (Slaughter et al., 2018). Conventional methods often require delayed data analysis and decision-making. Within pre-emergence (PE) spraying scenarios, drones have demonstrated a remarkable ability to control weeds, achieving efficiencies between 98% and 100% in fields with increased soil moisture and lower levels of straw. It's advised to highlight drone application for PE spraying due to its vital role in managing weeds effectively. In contrast, the effectiveness of post-emergence (PoE) spraying in causing weed damage varies widely, from 10% to 70%, indicating a noticeable resistance among weeds to the post-emergence herbicides used in this research (Y. Chen et al, 2018). UAVs equipped with advanced sensors and GPS technology can precisely target specific areas, reducing herbicide wastage and minimizing environmental impact (Anderson et al., 2018). In contrast, conventional ground-based methods may be less accurate in targeting herbicide application. UAVs can cover large areas quickly, potentially reducing labor costs and time spent on herbicide application (Lelong et al., 2008). Traditional methods may require more time and resources. UAVs can access challenging or remote terrain, making them suitable for hard-to-reach areas (Hunt et al., 2018). Conventional methods may struggle in such conditions. UAVs can also capture data about crop health and weed distribution simultaneously, allowing for data-driven decision-making (Dandois and Ellis, 2010). This integration is harder to achieve with conventional methods. UAVs can reduce herbicide drift and over-application, potentially minimizing environmental harm (Pfender et al., 2015). Conventional spraying methods may result in more herbicide dispersion.

4. Different herbicides dispersed using UAVs

Using a drone to apply Fluro Xypyr-meptyl at a concentration of 20% EC, at a volume of 600 mL per hectare, significantly reduces weed growth and height (K. Zhang et al. 2018). A UAV armed with the herbicide combination of diflufenican and isoproturon shows significant effectiveness in controlling weeds, achieving more than a 98% reduction in species like bedstraw (Galium aparine) and Japanese foxtail within wheat fields (Y. Chen et al. 2018). Applying isoproturon clodinafop-propargyl meso-sulfuron herbicides using a UAV shows similar weed control results as using a knapsack sprayer. Yet, the knapsack sprayer application of meso-sulfuron isoproturon clodinafop-propargyl is shown to be a more efficient method for controlling Japanese foxtail weed more so than its Unmanned Aerial Vehicle equivalent. At the same time, using UAVs to apply diflufenican + isoproturon leads to a 60% decrease in Japanese foxtail seedlings and a 50% decrease in shepherd's purse. In comparison, using a knapsack sprayer results in approximately 75 perecnt reduction in Japanese foxtails and 80 percent reduction in shepherd's purse. Shepherd's purses were planted in a different test plot. Moreover, using UAV technology with a combination of flufenacet, diflufenican, and flurtamone can effectively manage 70% of Japanese foxtail and 80% of shepherd's purse. Conversely, when using a knapsack sprayer, the reduction in Japanese foxtail is less than 85% and 80% in shepherd's purse (Y. Chen, 2018). The use of UAV for applying clodinafop-propargyl, mesosulfuron and isoproturon, herbicides at varying rates results in around 68% and 72% injury rates, while a knapsack sprayer causes 80% overall injury. In a different field, the use of UAVs is being applied. A reduced amount of herbicide combinations causes approximately 48-50% damage to Japanese foxtail weeds, while a higher amount results in 62-65% harm or damage done to the body. Furthermore, a 68% success rate is shown by the knapsack sprayer (C. Hiremath,2024).

Table 3: Comparison of UAV herbicide sprayers with conventional sprayers

5. Efficiency of herbicide using UAV technology

The effectiveness of Unmanned Ariel Vehicle sprayers is now 60 times greater than knapsack sprayers. Pre emergence treatments using UAVs and Post emergence treatments with knapsack sprayers exhibit enhanced weed control efficacy through different cases. Notably, knapsack sprayer treatments cause 56 to 64 percent injury to japanese foxtail, whereas UAV treatments result in only 20 to 40 percent injury (Y. Chen, 2019). Compared to previous methods, UAV applications are currently 200 percent more effective in detecting and managing weedy areas. Although UAVs treat 20 to 60 percent smaller areas than ground-based approaches, ground-

Attribute	UAV Sprayers	Boom Sprayers	Knapsack Sprayers	Citation
Application efficiency	High precision; uniform application	High efficiency in large fields	Suitable for small areas; moderate precision	Shi, Y., et al. (2018).
Cost	High initial cost; low operational cost	Moderate to high initial and operational cost	Low initial cost; high labor cost	Wolf, R.E., & Buhler, W.D. (2004).
Labour requirement	Low; automated operation	Moderate; requires skilled operator	High; labor-intensive	Giles, D.K., et al. (1996).
Environmental impact	Low drift; reduced chemical usage	Moderate drift; potential for runoff	High drift; less efficient	Felsot, A.S., et al. (2011).
Operational flexibility	High; can operate in difficult terrain	Low; limited to accessible large areas	High; very flexible in small and complex areas	Miller, P.C.H., & Butler Ellis, M.C. (2000).
Coverage area	Moderate; dependent on battery life and payload	Very high; covers large fields efficiently	Low; suitable for small areas	Shi, Y., et al. (2018).
Spray accuracy	High; GPS and automated controls	High; consistent spray pattern	Moderate; depends on operator skill	Zhang, C., et al. (2016).
Maintenance	Moderate; requires technical expertise	Moderate to high; regular calibration needed	Low; simple mechanical maintenance	Miller, P.C.H., & Butler Ellis, M.C. (2000).
Safety	High; remote operation reduces human exposure	Moderate; operator exposure to chemicals	Low to moderate; high exposure risk	Felsot, A.S., et al. (2011).

based treatments cover only 2 to 3 percent of the site, whereas UAVs miss 26% of the weedy region. UAV treatments surpass broadcast methods by 12 percent at 14 days after treatment (DAT) and by 25 percent at 28 DAT for highly aggregated weed densities. However, the effectiveness of UAV treatments declines by 15 percent at both 14, 28 days after transplanting for denser weed patches with a more homogeneous distribution (A. Chlingaryan, 2018). The study findings exhibit that UAV Integrated Spraying is 0.3 to 3 times effective than broadcast ground-based sprays in identifying and evaluating weedy target areas. Despite this advantage, ground-based applications cover nearly the complete experimental zone but miss 2 to 3 percent of the targeted weed patches, whereas UAV applications now dodge up to 26% of the intended weedy area (P. Chen, 2020). Compared to knapsack sprayer operation, which uses 140 Litre/ha of water, UAV spraying achieves a higher percentage of splash drops at 37.4 Litre/ha, marking a fourfold increase. These results suggest that UAVs, rather than backpack sprayers, can effectively administer herbicides (D. Martin, 2020). Currently, an AGRAS MG -1 equipped with 4 nozzles, a 5.0 m swath, and spraying at a rate of 10 L/ha at a speed of 5.56 m/s covers approximately 4 hectares per hour. This efficiency noticeably overtakes that of a knapsack sprayer in terms of volume (J.P.A.R. da Cunha, 2021). Researchers assert that compared to droplets noticed in ground trials (10–40 droplets per cm), UAV trials demonstrate smaller droplet sizes and greater coverage (>60 droplets per cm). Due to its reduced volume and enhanced precision relative to traditional ground techniques, UAV testing achieves more uniform vertical droplet distribution and offers capabilities for spot or band spraying, which are advantageous for drift control and minimization (J.L. Gibbs, 2021). The use of unmanned aerial vehicle (UAV) technology has been shown to enhance the efficiency of herbicide application in agricultural practices. Zhang et al. (2017) demonstrated the design and testing of a six-rotor UAV electrostatic spraying system for crop protection, aiming to improve pesticide use efficiency during multi-rotor UAV spraying. This technology offers a promising approach to optimize the application of herbicides, potentially leading to more effective weed control. Furthermore, the study by Faria et al. (2018) highlighted the high efficiency of herbicides and their low costs compared to other methods, emphasizing the advantages of this technology.

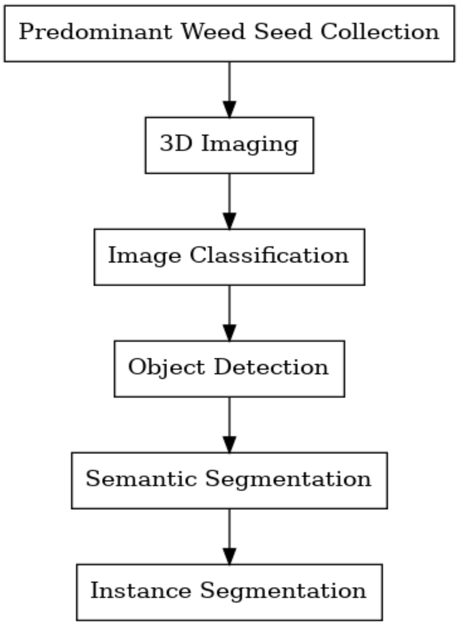
Table 4: Major UAVs used to map weeds

UAV Model	Manufacturer	Sensor Type	Weed Mapping/Detection Method	Flight Time	Battery Type	Payload Capacity	Weight	Reference/Citation
DJI Phantom 4	DJI	RGB Camera	Image Processing	30 minutes	LiPo 4S 5350 mAh	1.2 kg	1.38 kg	Peña, J.M., et al. (2013).
Parrot Sequoia	Parrot	Multispectral Camera	Spectral Analysis	25 minutes	LiPo 3S 2700 mAh	0.2 kg	0.72 kg	Torres-Sánchez, J., et al. (2015).
SenseFly eBee	SenseFly	Multispectral Camera	NDVI Analysis	50 minutes	Li-ion 3S 2150 mAh	0.55 kg	0.69 kg	Lelong, C.C.D., et al. (2008).
AgEagle RX-60	AgEagle	Multispectral Camera	Vegetation Indices	45 minutes	LiPo 4S 16000 mAh	2.5 kg	2.0 kg	Zhang, C., et al. (2016).
PrecisionHawk Lancaster	PrecisionHawk	Multispectral Camera	Image Classification	45 minutes	LiPo 4S 6600 mAh	1.1 kg	2.2 kg	Lottes, P., et al. (2017).
Trimble UX5	Trimble	RGB and NIR Cameras	Machine Learning/Deep Learning	50 minutes	Li-ion 4S 6000 mAh	2.5 kg	2.5 kg	Pérez-Ortiz, M., et al. (2016).
DJI Matrice 100	DJI	Hyperspectral Camera	Spectral Analysis	40 minutes	LiPo 6S 4500 mAh	3.6 kg	2.43 kg	Nebiker, S., et al. (2016)
DJI Surveyor Pro	DJI	RGB and Multispectral Camera	Image Processing	25-30 minutes	LiPo 4S 5870 mAh	1.5 kg	1.39 kg	DJI. (2023).
DJI Mavic 3M	DJI	Multispectral Camera	Spectral Analysis	30 minutes	LiPo 4S 5000 mAh	0.5 kg	0.9 kg	DJI. (2023).
DJI Matrice 350 RTK	DJI	Multispectral Camera	NDVI Analysis	55 minutes	LiPo 12S 6800 mAh	2.7 kg	3.77 kg	DJI. (2023).
DJI Mavic 3E	DJI	RGB Camera	Image Classification	45 minutes	LiPo 4S 5870 mAh	0.5 kg	0.9 kg	DJI. (2023)
DRONI	Garuda Aerospace	Multispectral Camera	Image Processing	20-25 minutes	LiPo 6S 22000 mAh	-	-	Garuda Aerospace. (2023).

6. Weed mapping using Deep Learning

Traditional methods of weed detection are laborious and lengthy. With the advent of precision agriculture, there is a growing interest in leveraging deep learning to automate weed mapping.

Figure 3: Flow chart of deep learning architectures for weed detection



Deep Learning Architectures in Weed Mapping

Deep learning has revolutionized image analysis, with Convolutional Neural Networks (CNNs) being the most popular architecture for weed detection. Recent studies have utilized various CNN architectures, including AlexNet, VGGNet, ResNet, and more specialized networks such as U-Net and SegNet for semantic segmentation tasks. For instance, researchers have applied U-Net for segmenting weed patches in crop fields, achieving high accuracy in distinguishing between crops and weeds (Garcia et al., 2020). Another study utilized Faster R-CNN for object detection in real-time weed mapping, demonstrating significant improvements in speed and accuracy (Kamilaris & Prenafeta-Boldú, 2018).

Datasets and Training Techniques

The effectiveness of deep learning models is largely contingent upon the quality and size of the training datasets. Publicly available datasets, such as the WeedMap dataset, CWFID

(Crop/Weed Field Image Dataset), and the Sugar Beets dataset, have been extensively utilized for training weed detection models. (Lottes et al., 2017). Weed data is fundamental to the development and benchmarking of weed recognition methodologies. The choice of sensing technology significantly impacts the quality and scope of weed data collected, thereby shaping the evolution of weed management practices (Machleb et al., 2020). Although various sensing techniques, such as ultrasound, light detection and ranging (LiDAR), and optoelectronic sensors, have been employed for basic differentiation between weeds and crops, image-based weed recognition has attracted considerable interest due to advancements in imaging technologies. Multispectral imaging captures light energy across specific wavelength ranges or bands of the electromagnetic spectrum, enabling the acquisition of information beyond visible wavelengths (Farooq et al., 2018). For example, hyperspectral imaging captures numerous contiguous and narrow spectral bands, whereas near-infrared (NIR) imaging targets a specific portion of the infrared spectrum. In NIR imaging, chlorophyll in plant leaves absorbs red and blue visible light while reflecting near-infrared light. The growing use of low-cost RGB cameras, coupled with significant advancements in computer vision, has made RGB images particularly popular for weed recognition (e.g., Olsen et al., 2019). Moreover, some studies have combined depth information (the distance between the image plane and each pixel) with RGB images using sensors such as the Kinect v2, leading to enhanced segmentation accuracy—from 76.4% for color-only images to 96.6% for broccoli detection (Gai et al., 2020)

Data augmentation

Data augmentation in weed mapping plays a crucial role in overcoming the challenges of obtaining large-scale, labeled weed image datasets for robust identification systems. While traditional methods like chemical herbicides are costly and environmentally unfriendly (Daniel, Steininger.,2023), recent advancements leverage generative adversarial networks (GANs) and diffusion probabilistic models to generate synthetic weed images for training deep learning models effectively (Dong, Chen.,2022). These approaches enhance sample diversity and fidelity, leading to improved model performance in weed classification tasks (Paolo, Fraccaro.,2022) Additionally, the use of Unmanned Aerial Vehicles (UAVs) for imagery collection, combined with deep learning methods, demonstrates high accuracy in automatically detecting weeds in agricultural fields, such as winter wheat, showcasing the potential for operational use and real-world impact in agronomic decision-making.Data augmentation techniques, including rotation, flipping, and color jittering, are commonly employed to enhance dataset diversity. Transfer learning, where models pre-trained on large datasets like ImageNet are fine-tuned on specific weed datasets, has also proven effective in improving model performance (Sa et al., 2017).

Performance Metrics and Evaluation

The performance of deep learning models for weed mapping is evaluated using metrics such as precision, recall, F1-score, Intersection over Union (IoU), and accuracy. For instance, a study reported an IoU of 0.85 using a U-Net model for weed segmentation in sugar beet fields, indicating high model reliability (Milioto et al., 2018). In binary image classification, where each input sample is labeled as either positive (P) or negative (N), there are four possible outcomes: (1) If a positive sample is correctly identified as positive, it is a true positive (TP). (2) If a negative sample is incorrectly identified as positive, it is a false positive (FP). (3) If a negative sample is correctly identified as negative, it is a true negative (TN). (4) If a positive sample is incorrectly identified as negative, it is a false negative (FN) (Machleb et al., 2020). Using these definitions, several key metrics are commonly used to evaluate algorithm performance. Accuracy is the proportion of correct predictions (#TP + #TN) out of all predictions (#P + #N). Sensitivity, or recall, is the proportion of correctly identified positive cases (#TP) out of all actual positive cases (#TP + #FN). This metric shows the algorithm's ability to detect weeds, where a low sensitivity means many weeds are missed, and a sensitivity of 1 indicates perfect detection. Precision is the proportion of correctly identified positive cases

(#TP) out of all predicted positive cases (#TP + #FP), indicating the level of off-target detection or crop damage. Specificity is the proportion of correctly identified negative cases (#TN) out of all actual negative cases (#TN + #FP), showing the algorithm's tendency to avoid false positives. The F-score (or F1 score) combines precision and recall,

calculated as: $F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$

Binary classification models typically produce continuous predictions, requiring a threshold to classify samples as positive or negative. Adjusting this threshold allows for trade-offs among metrics. A receiver operating characteristic (ROC) curve illustrates sensitivity versus 1-specificity across various thresholds, whereas a precision-recall (PR) curve depicts precision against recall. A high area under these curves (AUC) signifies a superior model. In the context of multi-class classification, these metrics can be computed for each individual class, and the mean values can be employed to evaluate overall performance (Farooq et al., 2018). In single-class object detection tasks, samples are associated with objects within bounding boxes. Intersection over Union (IoU) is defined as the intersection area divided by the union area of the predicted and ground truth bounding boxes. If the confidence value of a predicted bounding box exceeds a threshold and its IoU with the ground truth exceeds 0.5, it is a TP; if the confidence is high but IoU is low, it is an FP; if both confidence and IoU are low, it is a TN; if confidence is low but IoU is high, it is an FN. Precision and recall metrics measure detection quality, and varying the threshold creates a PR curve. Average precision (AP) summarizes the PR curve quality, calculated as the area under the curve. Different IoU thresholds, such as 0.5 (AP50) and 0.75 (AP75), yield different AP values. For multi-class detection, these metrics are computed for each class, with the mean average precision (mAP) representing overall performance (Olsen et al., 2019). In segmentation tasks, each sample is a pixel. Metrics like mean accuracy (mAcc), recall, precision, and F-score are derived similarly. Grouping pixels into regions allows the calculation of metrics such as mean average precision (mAP) and mean IoU (mIoU) (Li et al., 2019).

Future Prospects and Uses of UAV Technology in Weed Control

The review article discusses the existing status and possibilities of UAV technology for weed management. Based on this basis, various potential scopes and applications might be imagined

Integration with IoT and Smart Farming:

Future UAV systems might interact with IoT devices and smart agricultural platforms, allowing for real-time data collecting and analysis. This would enable faster decision-making and automatic reactions to weed detection.

Enhanced sensor technologies:

The development of more modern sensors, such as LiDAR and thermal cameras, may increase weed identification accuracy in a variety of environments. These sensors may give extra data layers, increasing the robustness of weed detection systems.

Autonomous UAV Swarms:

The deployment of many UAVs operating together might improve coverage efficiency and shorten operation durations. These swarms might communicate and collaborate in real-time, enabling large-scale weed mapping and pesticide delivery.

Precision agriculture with variable rate technology (VRT):

UAVs might relate to VRT systems to provide accurate pesticide delivery at varied rates. This would optimize pesticide use depending on weed density and crop requirements, lowering costs and minimizing environmental effect.

As UAV technology becomes more ubiquitous, clear rules and procedures will be required. These laws will enable the safe and effective use of UAVs in agriculture by addressing issues such as airspace control, privacy, and chemical application guidelines.

Commercialization and Industrial Adoption:

The development of low-cost UAV systems and services designed for small to medium-sized farms has the potential to increase industry adoption. Partnerships with agricultural enterprises and technology suppliers might help commercialize UAV-based weed control solutions.

Education and Training Programs:

Establishing educational programs and training for farmers and agricultural professionals on UAV technology and its uses has the potential to speed acceptance and effectiveness. These projects might include UAV operation, data analysis, and integration with existing farming techniques.

Cross-disciplinary Research and Collaboration:

Collaborations among agronomists, engineers, data scientists, and environmentalists might result in novel solutions and advances in UAV technology. Interdisciplinary research might solve complicated difficulties and increase the overall efficacy of weed management strategies.

Conclusion

The integration of Unmanned Aerial Vehicles (UAVs) into weed management practices represents a significant advancement in agricultural technology. This review has comprehensively examined the use of UAVs for weed mapping and herbicide spraying, highlighting the various types of UAVs and sensors employed, the methods for weed detection and herbicide application, and the comparative advantages of UAV technology over conventional methods. UAVs offer unparalleled precision and efficiency in weed detection and herbicide spraying. The ability to equip UAVs with Lidar, thermal, multispectral, hyperspectral, and RGB cameras allows for high-resolution data collection and accurate weed mapping. This precision facilitates targeted herbicide application, reducing the overall use of chemicals and minimizing environmental impact. Different types of UAVs, including multi-rotor, fixed-wing, and hybrid drones, provide flexibility and adaptability to various agricultural needs and field conditions.

The application of deep learning techniques has further enhanced the capabilities of UAVs in weed mapping. Advanced algorithms and convolutional neural networks enable the analysis of complex datasets, improving the accuracy of weed detection. The use of large, annotated datasets and data augmentation techniques enhances the robustness of these models, leading to better performance in real-world scenarios. Comparative studies between UAV-based and conventional weed management methods demonstrate the superiority of UAVs in terms of cost-efficiency, environmental sustainability, and operational flexibility. UAVs can operate in diverse climatic and edaphic conditions, making them a versatile tool for precision agriculture. The targeted application of herbicides using UAVs not only reduces chemical usage but also ensures more uniform coverage and better penetration in dense crop canopies.The efficiency and persistence of herbicides applied via UAVs have shown promising results, with UAV applications achieving comparable or superior weed control and crop yield outcomes compared to traditional methods. This efficiency is further enhanced by the ability of UAVs to cover large areas quickly and reduce the need for manual labor, making them an attractive option for large-scale farming operations, incorporating drone technology for herbicide application and weed detection in contemporary agriculture marks a significant advancement.

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