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Mapping and monitoring of weeds using unmanned aircraft systems and remote sensing

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Abstract: Effective weed management relies on frequent field monitoring, which is difficult to perform in vast areas. Integrating red-green-blue, thermal, hyperspectral, and multispectral sensors with unmanned aircraft systems and artificial intelligence ensures better results in managing the weed menace. Since India depends largely on agriculture, it is still a long way from implementing more advanced weed management methods. Mapping and surveillance of weeds in croplands by employing remote sensing will lead to varied herbicide application rates, thus reducing its overuse. This study reviews the practical application of remote sensing methods and unmanned aircraft systems in weed mapping.

Keywords: UAS; weed mapping; artificial intelligence; deep learning; sensors

In the 21st century, humans face the key challenge of providing food to the growing global population along with greater concern on preserving the environment. Biotic threats like weeds, insects, and diseases can influence crop yield, quality, and operational cost (Sathishkumar et al. 2022). Of all these factors, weeds reduce crop yield the most (Esposito et al. 2021). Weeds compete for sunlight, space, nutrients, water, and carbon dioxide with crops, reducing crop yield (Pazhanivelan et al. 2015). Combined, weeds, insects, and pathogens account for a 20–40% reduction in global crop productivity (Sharma et al. 2017). Weed interaction causes drastic yield reduction in all important food and non-food crops such as onion (90%), maize (40%), soybean (37%), rice (37%), cotton (36%), potato (30%) and wheat (23%) (Denisow-Pietrzyk et al. 2019). Numerous weed-management methods can reduce these detrimental effects, including hand weeding, herbicides, sustainable strategies, machines, and artificial intelligence (AI) (Roslim et al. 2021).

The global population is increasing exponentially and is estimated to reach 9 bil. by 2050. To meet the huge demand for food for the increasing population, agriculture needs to be revolutionised by using newer technologies (Jin et al. 2022). India is the most populated (1.42 bil.) country, with a current food grain production of 329.7 mil. t and a projected pop-

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ulation of 1.67 bil. by 2050. To provide food to this growing population, modern technologies should be adopted. While India depends on agriculture for its livelihood, it has to adopt modern technologies for maximizing the food production. Unmanned aircraft systems (UAS), photogrammetry, and remote sensing are being used by developed nations in precision agriculture (Colomina & Molina 2014).

Although weeds grow in patches, traditional practices involve managing the overall field. Spot application of herbicides reduces input wastage, whereas their application in large areas manually is impractical (Zhang et al. 2022). Minimising herbicide usage to reduce environmental impact while sustaining production and quality is a key challenge. One probable approach to meet this goal is site-specific weed management (SSWM), although reliable weed-recognition strategies are required (Louargant et al. 2018). Herbicide application at variable rates can be achieved by recognition of weed patches in croplands using remote-sensing technology (Oliveira et al. 2020).

To achieve SSWM, the integration of newer technologies like drones, AI, robotics, and sensors is required (Huang & Reddy 2015). Robotic weed management depends on the reliable detection of weeds in crop fields (Hu et al. 2021a). Robots have thus far been employed only in small farming systems (Oliveira et al. 2020).

Manual weed detection makes it difficult to mimic weeds at earlier stages of crops. Using spectral difference, UAS fitted with sensors could recognise the mimic weeds (Berni et al. 2009). UAS imagery helps better categorise weeds in earlier stages where weed and crop have similar morphology (Roslim et al. 2021). By employing UAS and remote sensing, researchers can obtain real-time, high-resolution data that enable proactive decision-making and targeted interventions (Singh et al. 2020). Deep learning neural networks could be used in the machine learning subset of automated sprayers to locate weeds and to apply herbicides precisely in the individual map cells (Jin et al. 2022). This review overviews precision weed mapping using advanced drones, sensors, and deep learning.

UNMANNED AIRCRAFT SYSTEMS AND THEIR TYPES

An unmanned aircraft system is an aircraft that can fly without a pilot and is controlled by a receiver. UASs are the main choice for quick and precise *in situ* data collection (Mancini et al. 2019). Based on the sensor fixed on the UAS, it may be used for varied purposes (Esposito et al. 2021; Pazhanivelan et al. 2023). Unlike satellites, UAS will offer only spatial and temporal resolution (Manfreda et al. 2018).

Saeed et al. (2018) categorised UAS into Horizontal Take-off and Landing (HTOL), and Vertical Take-off and Landing (VTOL) types. VTOL is further subdivided into single-rotor and multi-rotor types (Darvishpoor et al. 2020).

Horizontal Take-off and Landing (HTOL). Horizontal Take-off and Landing types of UAS have fixed wings. It is otherwise known as a fixed-wing aircraft (Figure 1). It uses its flaps/wings to produce lift due to forward movement (Hassanalian et al. 2017). The payload capacity of fixed-wing aircraft is comparable to that of rotary-wing aircraft. Fixed-wing aircraft are ideal for data acquisition in large areas and are fitted with higher-resolution cameras for better mapping (Barber et al. 2006; Velusamy et al. 2022).

The fixed-wing platform has lower operating costs, increased flight endurance, and the ability to operate under adverse conditions (Panagiotou & Yakinthos 2020). Flying at high speed makes concurrent weed detection, decision-making, and precise herbicide application problematic. Furthermore, it needs a catapult launcher or long runway to reach the perfect take-off speed (Darvishpoor et al. 2020).

Figure 1. Fixed-wing drone (Radoglou-Grammatikis et al. 2020)

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Figure 2. Different types of HTOL drones (Radoglou-Grammatikis et al. 2020)

Vertical Take-off and Landing (VTOL). Vertical Take-off and Landing platforms are equipped with propellers and do not need a runway. VTOL is also known as rotary wing aircraft due to its propellers. These types of UASs employ their propulsion for take-off and landing (Darvishpoor et al. 2020). Rotary-wing aircraft are further classified based on their number of propellers into the mono copter, tri copter, quadcopter, hexacopter, octocopter, etc. Figure 2 shows different types of VTOL drones. The ability of VTOL to hover at a place and perform quick movements enables meticulous field inspections. Using VTOL, developing weed maps with greater resolution is possible (Xiang et al. 2011). Limited payload and shorter endurance are major drawbacks of rotary-wing platforms.

ADVANCEMENTS IN SENSOR TECHNOLOGIES FOR PRECISION WEED MAPPING

Conventional methods of weed management, i.e. manual and chemical strategies, are laborious and costly. To overcome labour shortage, advances in weed management are essential. Automated weed detection and visualisation are crucial steps for providing alternatives to these traditional approaches (Li et al. 2021).

In precision farming, creating weed maps is the main function of UAS. Tracking and mapping weeds in crop stands are necessary to implement precision agriculture approaches, i.e. patch spraying (Pignatti et al. 2019). Remote-sensing imageries offer information on weed infestation in the crop stand by examining the variation in spectral properties of weeds and crops, which helps in need-based herbicide application. Weed mapping is successfully made by detecting crops and weeds' reflectance values. Each type of crop has specific reflectance values. Thus, it differentiates crops and weeds, and weed mimicry has been avoided (Kingra et al. 2016).

Developments in sensor potentialities have upgraded the reliability of weed detection and classification. Dynamic algorithms and object-detecting sensors utilise neural networks and AI for real-time image processing and decision-making (Thorp & Tian 2004; Sulaiman et al. 2022).

Enhancing the efficiency of agricultural inputs has become a crucial challenge in crop production. Recently, spectral imaging has become an adaptive tool to evaluate crop stands and assess herbicide needs (Reckleben 2014). Spectral imaging sensors are classified as red-green-blue (RGB), multispectral, hyperspectral, and thermal sensors. Some image-capturing sensors used in precision agriculture are listed in Table 1.

RGB imagery. The images with an array of red-green-blue bands produce the RGB imagery (Prey et al. 2018; Singh et al. 2019). RGB imagery is the visible spectrum image that utilises the light spectrum of 390–720 nm (Esposito et al. 2021). RGB imaging greatly enables weed species detection and differentiation (Lambert et al. 2018). Cameras having a resolution of 3–12 megapixels are employed to identify and differentiate the weed species according to their RGB colours and depth information of the plant size, cotyledons, leaf shape, leaf count, colour, branch, flower, fruit, and trunk (Rosell-Polo et al. 2015; Madsen et al. 2020). Using RGB imageries, vegetation indices, i.e. Green/Red Vegetation Index (GRVI), Excessive Greenness (ExG), and Greenness Index (GI) can be computed with higher accuracy (Xue & Su 2017).

Using RGB imageries, Pahikkala et al. (2015) found *Avena sativa* admixed with various weed species. With the help of computer vision, RGB images were used in deep-learning neural networks to differentiate weed species and crops (Roslim et

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Table 1. Image-capturing sensors used in agriculture

Sensors	Attributes	Opportunities	Drawbacks
RGB (Jack et al. 2019)	Dimensions, colour, form, edges, and texture	Faster to recognise through visual inspection; affordable and miniature in size; lower Unmanned aircraft system (UAS) payload; more clarity	There are only 3 bands; challenging to identify more traits; hard to find abnormalities in datasets; demands high-resolution image
Multispectrum (Su et al. 2020)	Look and geometrical characteristics, normalized difference vegetation index (NDVI)	Feasible to gather more spectral ranges; offers enough details; utilisation of near infrared (NIR); provision of vegetation index data	Highly expensive; photos will be captured depending on the weather; pictures have some ideal limit of resolution
Hyperspectrum (Hafeez et al. 2022)	Ratio vegetation index (RVI), NDVI	Utilisation of thousands of narrow continuous spectral bands; multiple dimension data; recognising improved features; gathers the entire dataset	Desires modern computers; expensive and intricate; hard to apply; Enormous data storage is required; over payload

al. 2021). Data obtained from the RGB sensors can be processed using vegetation index, deep learning methods, point clouds, and statistical methods (Hassler & Baysal-Gurel 2019).

With the help of RGB bands, developing weed maps for small crops has been challenging due to the spectral and morphology similarities between weeds and crops during their early development stages (Lopez-Granados 2011). Employing pixel-based image analysis will resolve these resemblances. Pixel-based image analysis also has some limitations, which can be cleared using object-based image analysis.

Red-green-blue imageries have some limitations: they perform better in circumstances where plant species vary in colour or morphology, and they offer only limited spectral data with the help of the three bands (red, green and blue) (Zhang et al. 2019). The quality of RGB imagery will deteriorate with reduced light (Rosell-Polo et al. 2015).

Multispectral imagery. Multispectral imagery refers to a situation where the number of spectral bands is 3–10 or fewer in each pixel (Roslim et al. 2021). Multispectral imaging involves acquiring pictures at a specified spectrum range utilising sensors that record the reflected radiation through a single optical pathway (Chen et al. 2002). Aerial multispectral imaging provides detailed and comprehensive data that was not acquired using RGB sensors. Even though it is invisible to the human eye, it delivers critical information about species-specific characteristics (Singh et al. 2019; Mink et al. 2020). Reliable weed maps are often generated by remote sensing utilising multispectral aerial imagery, especially during matured weed stages (Lopez-Granados 2011).

Many studies have indicated the potential of multispectral visuals on weed mapping. Stroppiana et al. (2018) employed UAS with a multispectral camera to map vegetation and weeds in cropland. Using multispectral imagery, healthy and diseased leaves could be distinguished according to fluctuations in reflectance at 670, 800, and 990 nm (Singh et al. 2019). Feyaerts and Van Gool (2001) employed multispectral imagery and neural networks to differentiate *Beta vulgaris* from five distinct weed species. Kim et al. (2001) employed multispectral fluorescence imaging to find the movement of herbicides within leaves through diffusion.

Nelson and Khorram (2018) used a Landsat-8 satellite (NASA, USA) that produces multispectral images with 11 bands, of which most of the bands have a resolution of 30 m except band 8-panchromatic (15 m), and bands 10 & 11 – TIRS 1 & 2 (100 m).

In a citrus orchard, Ye et al. (2007) evaluated the efficiency of multispectral weed mapping and the accuracy of 99.07%. The high spatial resolution of multispectral imageries, in combination with ground observation, resulted in species-level differentiation of weeds (Strecha et al. 2012). To examine weed categorisation by using multispectral drone images, Che'Ya et al. (2021) performed a study in which high-resolution multispectral data resulted in accurate weed detection.

However, because few spectral bands are employed in multispectral imaging, it is less effective in distinguishing crops and weed species. Another major limitation of multispectral imagery is its low spectral

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resolution (Ahmed et al. 2016). These limitations can be overcome by using hyperspectral imagery.

Hyperspectral imageries. Multispectral imageries fail to distinguish weeds at the species level due to their wider bandwidth. Hyperspectral aerial imaging has emerged as a novel remote-sensing technique to overcome this issue. Hyperspectral imaging sensors equipped with UAS are a valuable tool in weed mapping (Sulaiman et al. 2022) because of their extended ability to gather hundreds of narrow contiguous bands for each pixel[51]. Multispectral imaging has a bandwidth between 120 and 150 nm, whereas hyperspectral imaging is 1–15 nm (Borengasser et al. 2007). Table 2 shows the numerous hyperspectral sensors and their associated spectrum for crop species.

At both plants' early and late morphological stages, hyperspectral images produce extremely precise maps that could be employed to acquire an elaborate spectral value of target species at an intermediate scale (Lu et al. 2020). The effectiveness of weed mapping with 128-band hyperspectral imagery and a Random Forest algorithm to map leafy spurge (*Euphorbia esula*) and spotted knapweed (*Centaurea maculosa*) was evaluated by Lawrence et al. (2006).

Eddy et al. (2014) categorised weeds with better precision by utilising hyperspectral imageries. Huang et al. (2016) prepared a ground-based hyperspectral remote-sensing method for detecting crop injury from herbicides and distinguishing between herbicide-resistant and -sensitive weeds.

Eddy et al. (2008) grouped weeds within canola, wheat, and pea by adopting a ground-based hyperspectral technology and assessed the performance of this technique for weed recognition at the field level. Yang and Everitt (2010) used a hyperspectral-imaging technique and a minimum noise fraction (MNF) algorithm to map invasive weeds such as ashe juniper, broom snakeweed, and water hyacinth from associated plant species. All the plant species had similar reflectance under visible reflectance, while the invasive weeds could be distinguished from other species under near-infrared reflectance.

Table 2. Hyperspectral sensor and its associated spectrum for crop species

S. No.	Crop / Weed	Scientific name	Spectrum	Algorithm used
1.	Amaranth	*Amaranthus macrocarpus*	560 nm	Discriminant analysis (Ahmed et al. 2016)
2.	Pigweed	*Portulaca oleracea*	440 nm	
3.	Mallow weed	*Malva* sp.	710 nm	
4.	Nutgrass	*Cyperus rotundus*	720 nm	
5.	Liver seed grass	*Urochoa panicoides*	680 nm	
6.	Sorghum	*Sorghum bicolor*	850 nm	

An experiment on hyperspectral mapping to track plant entry which was performed by He et al. (2011), revealed that intruders could be discovered at the species level through the use of spectral characteristics displayed by the hyperspectral imaging technique. This accurately gives a baseline of invasive species dispersal for future monitoring and control efforts. With the help of the geographical dispersion of invaders, farmers organise long-lasting conservation programs to safeguard and sustain natural ecosystems.

Underwood et al. (2003) performed a trial to map ice plants and jubata grass in the Mediterranean ecosystems of California, which showed that hyperspectral visuals can accurately map nonnative plant species with MNF. A controlled laboratory experiment was carried out by Smith and Blackshaw (2003) to examine the potential of multispectral and hyperspectral sensors to distinguish between crop species (canola and wheat) and weed species (common lambs' quarters, wild mustard, redroot pigweed, wild oat, and green foxtail). The hyperspectral sensor differentiated all the species at 90% accuracy.

Pignatti et al. (2019) utilised hyperspectral data to differentiate maize from weeds and to discriminate between different species of weeds by exploiting leaf chlorophyll and carotenoid content and by using spectral indices. Liu et al. (2019) deployed a ground-moveable hyperspectral system to categorise carrot crops and weeds and examined how many spectral bands were necessary to attain high accuracy. According to Li et al. (2021), hyperspectral imaging with a machine-learning algorithm helps in the discrimination of various grass (yellow bristle grass and wind grass) and broad-leaved (giant buttercup and Californian thistle) weed species.

Apart from surface-level weed detection, Hestir et al. (2008) studied waterbodies to evaluate hyperspectral sensors. Perennial pepperweed and water hyacinth were mapped with moderate accuracy, and submerged aquatic vegetation was mapped with higher accuracy.

Goel et al. (2003) investigated the capability of hyperspectral aerial sensors in connection with nutri-

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ent levels to recognise the weed patches in maize. They determined that fluctuations in nitrogen levels altered the accuracy of weed categorisation because of the changes in chlorophyll levels. Because of the more complex nature of hyperspectral images than RGB and multispectral images, they are not used as much in precision farming (Farooq et al. 2018). Furthermore, its higher dimensionality and enormous and complicated data analysis made it difficult to acquire, process, and interpret (Lu et al. 2020).

Thermal imagery. Thermal image analysis involves the conversion of the hidden patterns of radiation of material into visible photographs for feature collection and analysis (Vadivambal & Jayas 2011). Although Infrared thermal imagery originally emerged for defence purposes, it is now commonly employed in numerous fields. In the farming and food sector, thermal imaging is often used to track drought stress, irrigation scheduling, discover weeds, diseases, and insects in plants, anticipate fruit production, assess the maturity of fruits, damage discovery in fruits and vegetables, and how temperature varies while cooking (Gomez-Candon et al. 2016). When coupled with AI and deep learning, thermal remote sensing could render real-time location-specific control methods feasible, such as plant and weed discrimination, production forecasting, and plant stress assessment (Ballester et al. 2018). Various thermal weed-control technologies were reviewed by Bauer et al. (2020), highlighting the need for further research into the use of automated imaging systems for weed/crop differentiation.

Commercial farming necessitates proper weed eradication, and the undiscovered value of thermal imagery gathered using UAS may enhance the site-specific approach to weed management (Delavarpour et al. 2021). Drone-based spectral, textural, structural, and thermal weed mapping was evaluated by Xu et al. (2023), who found that thermal measurements can significantly improve weed-mapping accuracy when combined with other remote-sensing data. This was further supported by Sagan et al. (2019), who tested and evaluated three UAV thermal cameras [ICI 8640 P (Infrared Cameras Inc., USA), FLIR Vue Pro R 640 (FLIR Systems, USA), and thermoMap (senseFly, Switzerland)] for their efficacy in precision agriculture, with all three cameras providing useful temperature data. Etienne and Saraswat (2019) applied machine-learning methods to automate weed detection using colour, multispectral, and thermal imagery and found them cost-effective. Rahkonen and Jokela (2003) highlighted using infrared radiometry to measure plant leaf temperature for thermal weed control.

Eide et al. (2021) used drone-based thermal infrared and multispectral cameras to detect glyphosate-resistant weeds and found that UAV-assisted thermal and multispectral remote sensing can accurately distinguish between glyphosate-resistant and -susceptible weed populations. However, they noted thermal reflectance measurements can be unreliable due to environmental conditions.

DEEP-LEARNING METHODS

Deep learning has been a valuable device in numerous scientific areas recently, such as natural language processing (Collobert et al. 2011), speech recognition (Graves et al. 2013), and computer vision (Jordan & Mitchell 2015; Krizhevsky et al. 2017). Perhaps the deep learning technologies employed in ML applications are deep convolutional neural networks, also known as DCNN (Jordan & Mitchell 2015). DCNNs utilise fewer artificial neurons than other neural networks, like the feed-forward method (Krizhevsky et al. 2017). DCNNs are very good at detecting objects and characterising images (Schmidhuber 2015). DCNNs did remarkably well when grouping a dataset of 1.3 mil. higher-resolution images with 1 000 classes in 2012 in an ImageNet competition (Krizhevsky et al. 2017). The usage of DNNs has been made easier by the accessibility of graphics processing units and the possibility of training on big datasets.

The most popular artificial neural networks that have been extensively utilised to recognise crops and weeds are convolutional neural networks (CNN). In contrast, there is a shortage of substantial training databases with ground-truth remarks. A typical remedy to the lack of training information is using semi-supervised training and a cut-paste image analysis method (Hu et al. 2021b). Performance metrics of some convolutional neural network algorithms are listed in Table 3.

Deep-learning methods improve the accuracy of weed-coverage estimation and minimise subjectivity in human-estimated data (Osorio et al. 2020). Farooq et al. (2018) found that using a DCNN for patch-based weed identification in hyperspectral images improved classification accuracy compared with traditional methods. Hu et al. (2021b)

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Table 3. Performance metrics of convolutional neural networks in dataset tested

S. No.	Neural Network Model	Crop	Precision	Recall	F1 score	Source
1.	YOLO-v3	Vegetable	0.971	0.970	0.971	Colomina & Molina (2014)
	CenterNet		0.956	0.950	0.953	
	Faster R-CNN		0.955	0.980	0.967	
2.	CenterNet2	Wheat	0.590	0.510	0.550	Louargant et al. (2018)
	Faster R-CNN		0.530	0.520	0.520	
	TridentNet		0.420	0.580	0.490	
	VFNet		0.480	0.520	0.500	
	YOLO-v3		0.970	0.450	0.620	
3.	GoogLeNet	Turfgrass	0.993	0.999	0.996	Colomina & Molina (2014)
	MobileNet-v3		0.973	0.963	0.968	
	ShuffleNet-v2		1.000	0.999	0.999	
	VGGnet		0.998	0.999	0.998	
4.	AlexNet-BLW	Alfalfa	0.970	0.980	0.970	He et al. (2011)
	AlexNet-Grass		0.980	0.970	0.970	
	GoogLeNet-BLW		0.980	0.970	0.980	
	GoogLeNet-Grass		0.980	0.980	0.980	
	VGGNet-BLW		1.000	0.980	0.990	
	VGGNet-Grass		0.980	1.000	0.990	
	ResNet-BLW		0.950	0.530	0.600	
	ResNet-Grass		0.320	0.890	0.470	
5.	YOLO-v3	Bahiagrass	0.550	0.460	0.500	Chen et al. (2002)
	Faster R-CNN		0.530	0.450	0.490	
	VFNet		0.480	0.390	0.430	
	AlexNet		0.990	1.000	0.990	
	GoogleNet		0.990	1.000	0.990	
	VGG		0.990	1.000	0.990	

opined that faster region-based are used for object recognition, quick segmentation, and semantic segmentation, respectively.

Jin et al. (2022) studied four different deep-learning methods [GoogLeNet (version 1), MobileNet (version 3), ShuffleNet (version 2), and VGGnet] to observe herbicide efficacy in turfgrass and ShuffleNet-v2 to be the most efficient and reliable. ShuffleNet-v2 was superior in different weed species according to their sensitivity to herbicide dosage. The impact of drought stress in the bahiagrass of Florida was assessed by Zhang et al. (2022) using DCNNs, who found that image analysis under drought will be more difficult when employing object-detecting neural networks.

Many characteristics, especially plant colour, leaf shape, size, and texture, are important for weed detection (Espejo-Garcia et al. 2020). However, environmental conditions like drought impact the morphological properties of leaves, which could affect the utility of machine-learning models (Zhang et al. 2022).

CHALLENGES IN ADAPTING UAS AND REMOTE SENSING

Unmanned aircraft systems in precision agriculture have critical challenges like payload, sensors, cost of UAS, flight duration, and data analytics (Huang & Reddy 2015). The devices and tools used to make precise decisions involve higher costs, making them unsuitable for small and marginal farmers (Sharma & Hema 2021). UAS mostly fly using energy from a battery. Some of the hybrid drones employ gasoline and batteries for flying. Batteries of UAS have an endurance of 10 to 30 min maximum. The endurance of battery life varies based on the payload capacity, camera power, altitude

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of UAS and weather conditions such as wind speed (Hardin et al. 2019). The primary influence of the deployment of UAS in farming is an expenditure encompassing a range of sensors, technology-driven programs, and the software required for data processing (Hardin & Jenson 2011). Numerous terabytes (Tb) of data need to be stored, processed, and analysed adequately using appropriate software. Atmospheric conditions that restrict UAS operations and their detection process are rainfall, snow, cloud cover, fog, and wind turbulence. There are strict regulations for UAS flying from the government side (Sharma & Hema 2021). The drone flying area is divided into three zones, i.e., *(i)* green zone, *(ii)* yellow zone, and *(iii)* red zone. In the green zone, there are no restrictions up to 400 feet from above ground level; the yellow zone has some restrictions on flying UAS over that zone. The remote pilot needs to get approval from Air Traffic Control (ATC), to fly the UAS over the yellow zone up to 200 feet from above ground level. Agricultural fields near airports and some areas marked as red zones that were restricted from flying the UAS by the government have law barriers. While operating UAS in densely vegetated areas, obstacle avoidance is mandatory to ensure the safety of the UAS system. These obstacle avoidance sensors are available with few of the costlier UAS. It should be mounted with all the UAS to avoid damage (Hardin et al. 2019).

FUTURE OF AI IN AGRICULTURE

In the future, using new lightweight materials will increase the endurance of the UAS, enabling it to accomplish tasks without any constant battery brakes. Microcontrollers, advanced sensors, the Internet of Things (IoT) with UAS, and big data analysis & cloud computing should be done to make precise decisions (Sharma & Hema 2021; Ghazali et al. 2022). Combined with machine learning, AI will address key issues like food safety and climate change (Patel 2023). It also reduces agricultural chemical dumping and enhances crop productivity and soil fertility (Naresh et al. 2020). Developing new lenses and sensors will help identify other diseases or parasites on plants or weeds that are hard to detect by current hardware. Equipping a UAS with a granule spreader can help it distribute seeds much faster, especially in rough terrains and big fields such as forests. Agricultural UASs will accomplish automatic task sequences such as spraying required water or herbicide on specific areas according to the generated map while following the route on the field (Kaya & Goraj 2020).

CONCLUSION

Farming is one of the key areas shaping the global economy, as it contributes to the long-term prospects of most of the population. This paper reviews the possible outcomes of deep learning techniques, spectral imagery, and UAS in agriculture, with a special emphasis on weed mapping. This holistic perspective aids in optimising resource allocation, minimising herbicides usage, and promoting environmentally friendly farming practices.

As we navigate the challenges of feeding a growing global population while addressing sustainability concerns, adopting UAS and remote sensing in weed management emerges as a crucial step toward achieving a balance between agricultural productivity and environmental stewardship. The ongoing technological advancements and collaborative efforts between researchers, industry stakeholders, and farmers promise a future where precision agriculture becomes an indispensable tool for sustainable and efficient food production.

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