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Review Article

Weeds Detection and Control in Rice Crop Using UAVs and Artificial Intelligence: A Review

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Abstract: Weeds are severe issues in rice farming and undesired plants that compete for water, light, space, and nutrients and consequently reduce crop yields. Weeds competition in rice crops can result in yield failure of up to 100% if weeds are not controlled. Furthermore, weeds will raise protection costs by harbouring other pests, such as diseases, insects, and nematodes that use weeds as alternate hosts. Rice fields are infested with grassy weeds, broad leaves, and sedges, among other weeds. Weeds detection is essential to identify the types of weeds in rice areas and make the precise decision to determine the method of weed control and reduce herbicide use. Chemical, biological, and mechanical weed control strategies such as hand-pulling, tillage and herbicide spraying are all part of the Integrated Weed Management (IWM) approach. The common practice in the rice field is using herbicides to control weeds. Still, this method has become ineffective due to frequently spraying with the same herbicide continuously, annually or more than once yearly for several years. Early detection is required to define the type of weeds in rice fields, make a precise decision on weed management methods, and prescribe the appropriate herbicide to the rice farmer. Artificial intelligence and unmanned aerial vehicles (UAVs) were primarily applied to identify the weeds in rice fields and herbicide spraying to control the weeds. UAVs, such as drones, have recently shown much potential in agriculture, such as crop health monitoring systems, assisting in planning irrigation schedules, estimating production data, and capturing weather analysis data and weed infestation. In Malaysia, UAVs are mainly utilized for nutrition and pesticide applications, particularly by smallholder farmers and industries. Integrating artificial intelligence, such as unmanned aerial vehicles with various sensors for weed detection methods, could ensure a better outcome in managing the weeds problem. This paper reviews the detection and control of weeds using UAVs and artificial intelligence technologies in rice crops.

Keywords: Weeds; Weeds Detection; Weeds Control; Unmanned Aerial Vehicles; Artificial Intelligence

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1. Introduction

One Weed becomes an expanding, continuous problem in every planting season in rice areas. It presents a significant problem in rice cultivation when they compete for space, light, and nutrients (Chauhan, 2020). Many types of weeds include sedges, grasses, and broadleaved weeds (Jamil *et al.*, 2018). On the other hand, the presence of weeds in the rice area will reduce the rice production and quality, especially during the cultivating moment with direct seeding, and it can cause severe crop yield losses if the weeds are uncontrolled (Chauhan, 2020; Kamath *et al.*, 2020).

Early detection of weed populations is essential to decide the best method to control the weeds in rice areas (Kamath *et al.*, 2020). The unmanned ground vehicle (UGV) and unmanned aerial vehicle (UAV) were used to control the weed to minimize labor usage and increase the quality of production (Bini *et al.*, 2020). Weed in rice fields can be controlled by many methods, such as manual weeding, mechanical weeding, and using (Renton & Chauhan, 2017).

Using herbicide spraying to eliminate weeds is a popular control method in the rice field because it is more effective than manual weeding (Renton & Chauhan, 2017). However, the effect of spraying herbicides depends on what tools were used to control the weed, either spreading by knapsack sprayer, power sprayer, or using unmanned vehicles (UAVs) to ensure the possibility of a better outcome in managing weed problem (Hu *et al.*, 2020; MacLaren *et al.*, 2020). Weeds population, herbicide spraying time, and herbicide dosage are the weed management factors important for controlling weeds using chemical control methods (Peerzada *et al.*, 2016).

Weeds detection, such as grassy weeds in rice areas, become a problem, especially in large-scale rice areas such as Paddy Estate FELCRA Seberang Perak. In actual practice, visual observations are widely used to detect weeds because of their general availability. Still, they are labour-intensive, which is not practical in the estate. However, the practice is not practical in the estate. Artificial intelligence and unmanned aerial vehicles (UAV) such as drones are the latest developments since they are considered an eye in the sky and have a vast potential to support agriculture in spatial data collection (Giacomo & David, 2018). The hyperspectral camera equipped with the drone with hundreds of spectral bands can capture images on the ground to identify weed species in the fields (Su, 2020).

2. Rice Cultivation in Malaysia

Rice (*Oryza sativa* L.), a C3 plant, is a staple food and carbohydrate source for more than half of the world's population, with 90% of it grown in Asia countries such as China, India, Brazil, Japan, Thailand, Vietnam, Cambodia, and Malaysia (Bista, 2018). According to the USDA, global rice output was around 475,988 million tons from 2013 to 2015 and is expected to rise to approximately 655,178 million tons by 2035 due to population growth (Koizumi, 2018).

Malaysia has produced over 2,500 million tons of rice yearly on 699,980 ha of land, with an average of four metric tons per hectare per planting season (Jabatan Pertanian Malaysia, 2020). The self-sufficiency level (SSL) for rice production, according to the Khazanah Research Institute (KRI), is around 70%. To meet Malaysians' annual rice consumption of 80 kg, or 26% of total daily calories, the government had to import rice from other nations such as Thailand, Vietnam, and Pakistan (Che Omar *et al.*, 2019).

The rice planted in Malaysia (Peninsular, Sabah, and Sarawak) was 699,980 hectares in 2020 (Department of Agriculture [DOA], 2020). Table 1 shows the total grown paddy areas from 2016 until 2020.

Table 1. Total Planted Area for Rice for the Year 2016 to 2020

Area /Year (ha)	**2016**	**2017**	**2018**	**2019**	**2020**
Peninsular (All paddy area)	**522,826**	**522,678**	**522,112**	**519,063**	**522,112**
Granaries Area (Peninsular)*	417,007	426,249	426,046	422,078	426,046
Sabah	41,733	42,157	42,442	43,546	42,442
Sarawak	124,211	120,713	135,426	109,261	135,426
Total	**688,770**	**685,548**	**699,980**	**671,870**	**699,980**

Source: DOA, 2020

There are twelve (12) granary areas in Malaysia, namely Muda Agricultural Development Authority (MADA), Kemubu Agricultural Development Authority (KADA), Integrated Agricultural Development Area (IADA) Kerian, IADA Barat Laut Selangor, IADA Pulau Pinang, IADA Seberang Perak, IADA Ketara, IADA Kemasin Semerak, IADA Pekan and IADA Rompin. New areas in Sabah and Sarawak, namely IADA Kota Belud and IADA Batang Lupar, were launched in 2017 as new granary areas, as shown in Table 2.

Table 2. Total Planting Areas for Granary Areas.

IADA	Rice Area (ha)
MADA	201,884
KADA	54,178
IADA Barat Laut Selangor	41,882
IADA KETARA	9,457
IADA Seberang Perak	27,745
IADA Kerian	41,822
IADA Kemasin Semerak	7,327
IADA Pulau Pinang	25,247
IADA Pekan	7,107
IADA Rompin	5,616
IADA Kota Belud	9,265
IADA Batang Lupar	1,143
Total	**426,046**

Sources: DOA, 2020

The planted area and rice productivity in Malaysia from 2016 to 2020 are depicted in Table 2.3. In general, the rice area shows a decrease in areas of rice planted, and the average rice production is between 70–75%. Malaysia imports approximately 20–24% of its rice from neighbouring countries. The average yield of rice crops at the national level for 2016–2020 was 3.75 to 4.18 metric tons/hectare (DOA, 2020).

Table 3. Annual Production of Rice Crop, 2016–2020

YEAR	2016	2017	2018	2019	2020
Population (million)	31.18	32	32.4	32.6	32.7
Planted Area (ha)	688,770	685,548	699,980	671,870	699,980
Production (million tons)	2.740	2.571	2.640	2.348	2.927
Average Yield (kg/ha)	3,978	3,750	3,770	3,496	4,183
Production of Rice (million tons)	1.766	1.656	1.700	1.514	1.886
Imports of Rice (million tons)	0.748	0.726	0.776	NA	NA

Sources: DOA, 2020

3. Weeds Problem in Rice Area

Rice can be cultivated in different ways, such as direct-seeded and transplanted-seeded (Bista, 2018). Direct-seeded rice is a resource conservation technique that saves 50% on water and labour (Chostner, 2017). Even though weeds are a big concern with direct-seeded systems, they are nevertheless commonly employed in Asia because of their low cost of production (Marasini *et al.*, 2018).

Malaysian Rice Development Institute (MARDI) produced certified seeds such as MR219, MR297, MR220 Clearfield, and MR315, already established cultivars in Malaysia (MARDI, 2020). However, weed infestation, pest and disease, water constraints, labour shortages, low land fertility, and climate change pose significant problems to Malaysian rice farmers (Bista, 2018; Dilipkumar *et al.*, 2020).

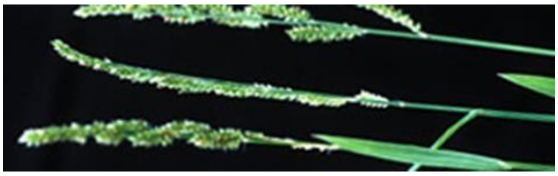
According to International Rice Research Institute (IRRI) there are twelve most troublesome weeds of rice such as *Leptochloa chinensis*, *Echinochloa crus-galli, Ischaemum rugosum, Echinochloa colona, Cyperus iria, Cyperus difformis, Eclipta prostrata, Fimbrisstylis miliacea, Ludwigia hyssopifolia, Oryza sativa* (weedy rice), *Schoenoplectus juncoides* and *Sphenocles zeylanica* (Rice Knowledge Bank, IRRI) (Figure 1).

The critical stage for controlling weeds in the rice plant is vegetative growth to the reproductive stage (Saad *et al.*, 2012). Due to weed density competition, rice development will be slowed, and maximum tillering will not occur (Yoshida, 1981). Water constraints due to climate change negatively impact cultivating areas, resulting in a shift in the distribution of weeds (Weed *et al.*, 2012).

Aside from that, substantial labor was required to control weeds in rice fields from planting until harvesting (Karim *et al.*, 2004). Drone technologies have the potential to increase the efficiency of chemical spraying in the agricultural business, as well as help alleviate workforce shortages and boost crop yield and performance (Bini *et al.*, 2020).

Cyperus iria

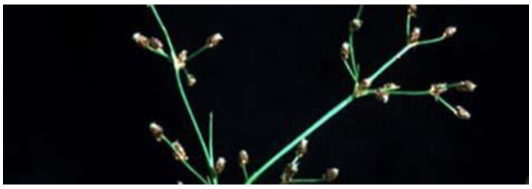
Cyperus difformis



Echinochloa colona

Echinochloa crus-galli

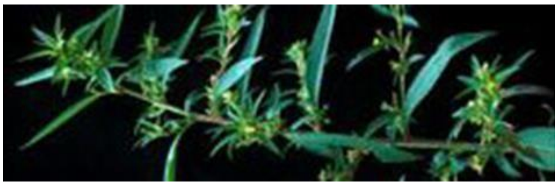
Eclipta prostrata



Fimbristylis miliacea

Ischaemum rugosum

Leptochloa chinensis



Ludwigia hyssopifolia

Oryza sativa

Schoenoplectus juncoides

Sphenoclea zeylanica

Figure 1. Twelve most troublesome weeds of rice in Asia (IRRI, 2015)

4. Weeds Management in Rice at Different Stages

Weed control is essential to prevent losses in yield production costs and to preserve good grain quality (Zimdahl, 2018). Specifically, weeds will decrease the yields by direct competition for sunlight, nutrients and water, increase production costs, and reduce grain quality. For example, the contamination of weed seeds in rice yield can cause deterioration of rice quality (Chauhan, 2020). Weed management should be practised during specific stages of rice production (IRRI, 2015).

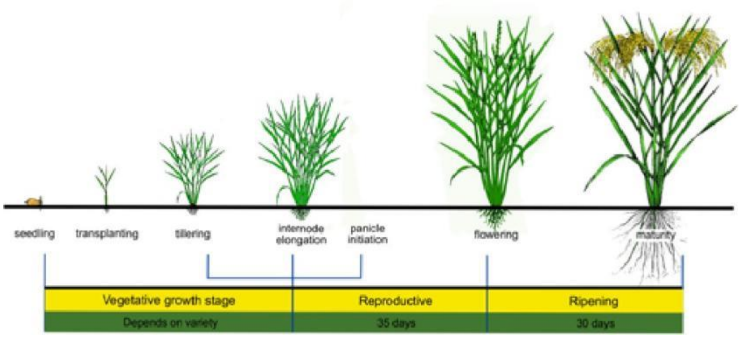


Figure 2. The growth cycle of a rice plant corresponds to the IRRI scale and sample structure (Fairhurst *et al.*, 2007; IRRI, 2015; Rosle *et al.*, 2021)

Rice plants usually take 100 to 120 days to mature, depending on the variety and location in which they are produced (Figure 2). The rice development stages are vegetative, reproductive, and ripening (Fairhurst *et al.*, 2007; IRRI, 2015; Rosle *et al.*, 2021) (Figure 1). Rice management is essential during those three stages to ensure a higher yield through correct planning concepts and execution at the appropriate times (IRRI, 2015). Additionally, rice plants need adequate nutrients, water, and sunlight to develop as cereal plants through each stage and generate a high yield (Chauhan *et al.*, 2017; Jabran, *et al.*, 2017).

Therefore, the vegetative stage is critical in the paddy growth cycle. Successfully controlling weeds at this stage can deliver a 95% weed-free yield (Sciences, 2015). This is in line with Kamath *et al.* (2020) because the effect of weeds in this stage will be at maximum if uncontrolled. However, suppose we fail to prevent weeds from spreading in the vegetative stage. In that case, they will dominate the area, leading to a lack of sufficient space, light, and nutrients to grow and develop (Chauhan, 2020). As a result, crops will experience uneven flowering and will not mature uniformly for the scheduled harvest (Mohidem *et al.*, 2021).

5. Early Detection and Monitoring to Control the Weeds

Weed also becomes a significant problem for the rice crop when the soil becomes a seed bank (Mahé *et al.*, 2020). Weeds are unwanted and undesirable plants that can reduce rice quality and production (Kamath *et al.*, 2020). Without proper control, rice production will be a total loss due to weeds (Chauhan *et al.*, 2020).

Weed infestation has been reported in transplanted, wet-seeded and dry-seeded rice areas (Peerzada *et al.*, 2016). In Malaysia, 5 to 85 per cent of production losses due to weed infestation are related to cultivation methods, season, water supply problems, weed density, and management practices (Dilipkumar *et al.*, 2020). The weeds become dominant plants in dry season rice cultivation due to water scarcity (Take-tsaba *et al.*, 2018). Weeds can also be distributed by the water and irrigation systems (Zimdahl, 2018).

Weeds became the host of various insect pests and infested the rice plant (Kamath *et al.*, 2020). Furthermore, the weed's odour will attract the insect herbivores to the crops and play an essential role in the host location by most insects (Capinera, 2005). Some insect pests can survive long-term and breed weeds (Peng *et al.*, 2020).

Weeds can be categorized as annual, biennial, or perennial and help determine the control methods (Zimdahl, 2018). Many types of weed infestation in rice areas include grassy weeds, broadleaves, and sedges (Jamil *et al.*, 2018). The types of weed infestation depend on the location and climate of the rice area (Dilipkumar *et al.*, 2020).

Weeds were controlled using cultivation methods, tillage, conventional herbicides, mechanical machines, and artificial intelligence (Esposito *et al.*, 2021). In the direct-seeded cultivation method, the weed infestation relied on weed management practices in the rice field (Saha *et al.*, 2021). Transplanted rice cultivation is most popular among farmers to manage the weed problem and control the quality of rice production. Still, the production cost is higher than direct-seeded methods in terms of the nursery, seedling uprooting, and transplanter machine (Hu *et al.*, 2019).

Weeds in rice fields can be controlled by manual weeding, mechanical weeding, and herbicides as an Integrated Weed Management (IWM) approach (Esposito *et al.*, 2021). The rice farmers highly rely on herbicides, especially in direct-seeded rice cultivation areas (Dilipkumar *et al.*, 2020). Effective weed identification techniques are essential to identify the recommended herbicides to control weeds (Kamath *et al.*, 2020). Otherwise, herbicide spraying is a prevalent control method in the rice field to eliminate the weeds. Still, this method becomes weed resistant to herbicide due to continuously spraying with the same type of herbicide (Jamil *et al.*, 2018). However, not all weeds will be solved by herbicide spraying (Dilipkumar *et al.*, 2020).

Early detection is essential to identify the type of weeds in rice fields and precisely determine the weed control method. Besides that, it will reduce input and labor usage (Renton & Chauhan, 2017). Site-specific weed control (SSWM) effectively reduces herbicide usage and environmental impact (Pflanz *et al.*, 2018). On the other hand, early season site-specific weed management (ESSWM) has been used in precision agriculture to detect weeds using new technologies to reduce herbicide usage and decrease the environmental impact (Torres-Sánchez *et al.*, 2013).

Tillage is also one of the popular methods rather than herbicide use to prevent the growth of weeds in rice areas using mechanical and machinery. Still, it can negatively impact crop growth and yield due to soil erosion and compaction (MacLaren *et al.*, 2020). Besides that, soil quality and organic carbon decreased when long-term deep tillage was implemented in a rice field (Hu *et al.*, 2021; Nandan *et al.*, 2019).

To date, monitoring and detecting weeds using geospatial technologies with machine learning, such as integrating robotics, artificial intelligence (AI), and various sensors, will better impact agriculture (Bini *et al.*, 2020; Oliveira *et al.*, 2020). These advanced technologies can minimize labor usage and improve production quality by using unmanned ground vehicles (UGV) and unmanned aerial vehicles (UAV) (Bini *et al.*, 2020).

6. Application of Artificial Intelligence and Unmanned Aerial Vehicles in Agriculture

The ability of human eyes to identify weeds in rice fields is limited. Artificial intelligence and drones are used in weed management to help overcome those mentioned limitations. Artificial intelligence is the use of machine learning to create computer programs that can teach a robot or actuator to accomplish a task specified by the programmer. Artificial intelligence (AI) can build an intelligent plant factory in which data from supply chains, design teams, manufacturing lines, and quality control is linked to creating highly integrated and intelligent systems (Mat Lazim *et al.*, 2020).

6.1. Artificial Intelligence in Weed Management

The agriculture sector is confronted with significant issues, including labor and land scarcity, as well as the impact of climate change on productivity (Chauhan, 2020). Challenges include a lack of agricultural land due to urbanization, a progressive drop in rural labour due to population ageing and migration, and industrial development destroying agricultural land (Zhang *et al.*, 2020). Furthermore, when climate change worsens, crop growth conditions such as temperature, precipitation, soil fertility, and moisture will vary (Koizumi, 2018).

To assist farmers in large-scale agriculture, the agriculture sector requires innovative technologies. Farmers in Malaysia are encouraged to embrace modern technology to improve the agriculture industry as part of the Industrial Revolution 4.0 (IR 4.0) initiative, which includes features such as the Internet of Things (IoT), autonomous robots, and artificial intelligence (Mat Lazim *et al.*, 2020).

Artificial intelligence is a technology that combines machine learning and the education of a robot to assist and speed up human operations in many areas, such as agriculture, food processing, supply chains, and quality control (Mat Lazim *et al.*, 2020). Artificial intelligence, such as unmanned aerial vehicles and autonomous vehicles (Machleb *et al.*, 2020), the thermal sensor (Al-doski *et al.*, 2016), and odour signals (Burgués *et al.*, 2021) are famous in crop operations such as in irrigation scheduling (Jimenez *et al.*, 2020), weed monitoring (Machleb *et al.*, 2020) and controlling, pest and disease mapping (Yuan *et al.*, 2021) to face agricultural challenges and application of precision agriculture practices in the field.

Artificial intelligence, such as autonomous mobile robots, can be utilized in the field for weed monitoring and control in the agricultural sector because of specific qualities such as self-guidance, weed detection and identification, precision intra-row weed management, and weed mapping (Machleb *et al.*, 2020). Artificial intelligence will deliver sophisticated knowledge to human civilization and the supply chain and increase the quality of agricultural goods as the internet, sensor networks, and big data grow (Zhao, 2020). Furthermore, using artificial intelligence in agricultural and food production will feed a growing population predicted to reach 10 billion people by 2050. (Gonzalez-De-Santos *et al.*, 2020; Kim *et al.*, 2019).

6.2. Artificial Intelligence with Machine Learning for Image Processing

Artificial intelligence is a rapidly developing computer technology that affects every aspect of our lives. Artificial intelligence will lead to fundamental changes in many professional fields, including agriculture, involving digital imaging and image recognition (Zhao, 2020). Various tasks in agriculture, such as disease detection in crops, precise spraying of pesticides, prediction of crop yield, estimation of soil texture, automatic grading of fruits, assessment of crop biomass, management of water balance in the irrigation system, and monitoring plant growth has been done using computer vision techniques as support by machine learning (Alfer’ev, 2018).

The data resources from artificial intelligence will be applied to machine learning to understand the content of digital images in agriculture, such as weed detection in rice fields (Kamath *et al.*, 2020). Image processing techniques using machine learning algorithms such as Random Forest Classifier, Support Vector Machine (SVM) and Convolutional Neural

Networks (CNN) are widely used to classify RGB, multispectral and hyperspectral images in agricultural areas (Al-doski *et al.*, 2013). In weed mapping and image classifier, they concluded that the SVM approach showed better classification performance than the Random Forest and neural network (Pflanz *et al.*, 2018). The machine learning approach includes a learning process in which the trained model can classify, predict, or cluster new examples (testing data) using the experience obtained during training (Liakos *et al.*, 2018). Figure 3 shows a typical machine-learning approach.

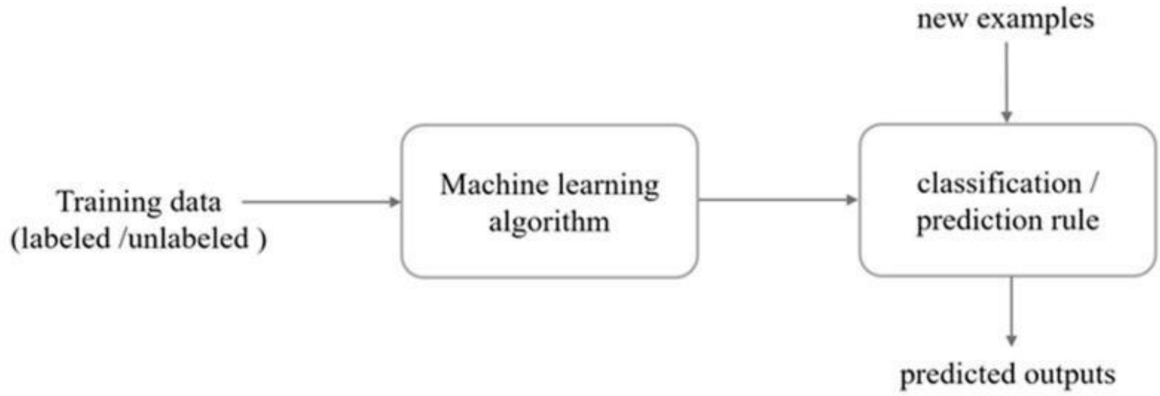


Figure 3. A typical machine-learning approach

7. Application of Unmanned Aerial Vehicles in Agriculture

Unmanned Aerial Vehicles (UAVs) or drones are like eyes in the sky commonly employed in agriculture to identify weeds, pests, and illnesses (Kaivosoja *et al.*, 2021). Besides that, drones are being commercialized for chemical spraying of insecticides and herbicides in agriculture, particularly in rice fields. According to Koot (2014), Deploying RGB and hyperspectral photos, the researchers investigated the possibilities of using UAVs in agricultural weed control systems in sugar beet and potato plants.

Drones can be equipped with sensors such as Red-Green-Blue (RGB), multispectral, hyperspectral, and thermal cameras to detect weeds in their early stages. Machine learning tools like ARGIS, ENVi, and QGis will be used to analyze the image from the data acquisition. To process the data accurately, high-spec gear must be considered.

7.2. Weeds Detection and Control using Unmanned Aerial Vehicles

UAVs or drones are remotely controlled aircraft with no human pilot on board, like an eye in the sky for agriculture, with advanced technologies that can collect spatial data from the ground (Giacomo & David, 2018). Drones can increase working capacity, working hours, accuracy, improved quality and productivity in many sectors, especially agriculture (Kim *et al.*, 2019).

Thus, the number of drones in agricultural applications is rapidly increasing with many platform types, controllers, sensors and communications methods (Kim *et al.*, 2019). Many types of drones are being used in agriculture applications, as summarized in Figure 4.

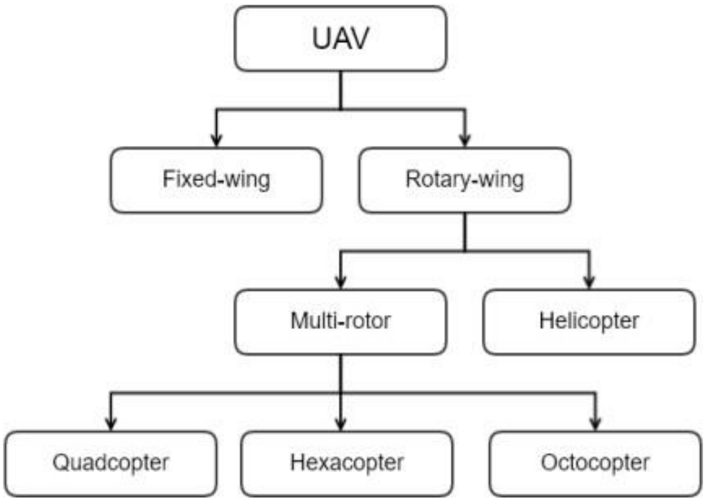


Figure 4. UAV platform types (Kim *et al.*, 2019)

Drones equipped with the Internet of Things (IoT) and integrated with machine learning can efficiently operate by farmers to gather real-time data and improve agriculture production (Saha *et al.*, 2018). Drones equipped with RGB, multispectral, or hyperspectral cameras are also used to capture aerial imagery. It can create a high spatial resolution image to get accurate digital image data and process in suitable software such as soil nutrients and vegetation (Andújar *et al.*, 2019).

Recently, drone technologies have been trendy among farmers in the rice industries in Malaysia to control insect pests and weed infestations in rice areas (Vanegas *et al.*, 2018). Instead of monitoring the weeds and pests, the drone is expanding its application to spray herbicides and pesticides in rice areas (Talaviya *et al.*, 2020). Besides that, drones can reduce pesticide use and increase efficiency (Kim *et al.*, 2019).

Drones with RGB and hyperspectral cameras are the technologies in precision agriculture. This approach is used in Site-Specific Weed Management (SSWM) to efficiently monitor and control weed infestation (Esposito *et al.*, 2021). Drone is widely used in crop and weed mapping because it efficiently manages agricultural crops. Weed population displays spatial variation within the crop types in mapping weed infestation to site-specific weed control and enabling the right of herbicide application (Pflanz *et al.*, 2018).

Drones with advanced sensors can determine crop stress and crop damage due to herbicide use and water stress (Talaviya *et al.*, 2020). To monitor agricultural fields, drones have become suitable platforms because of the moderate costs for application (Pflanz *et al.*, 2018). There are many types of drones in agricultural fields, as shown in Figure 6 below.

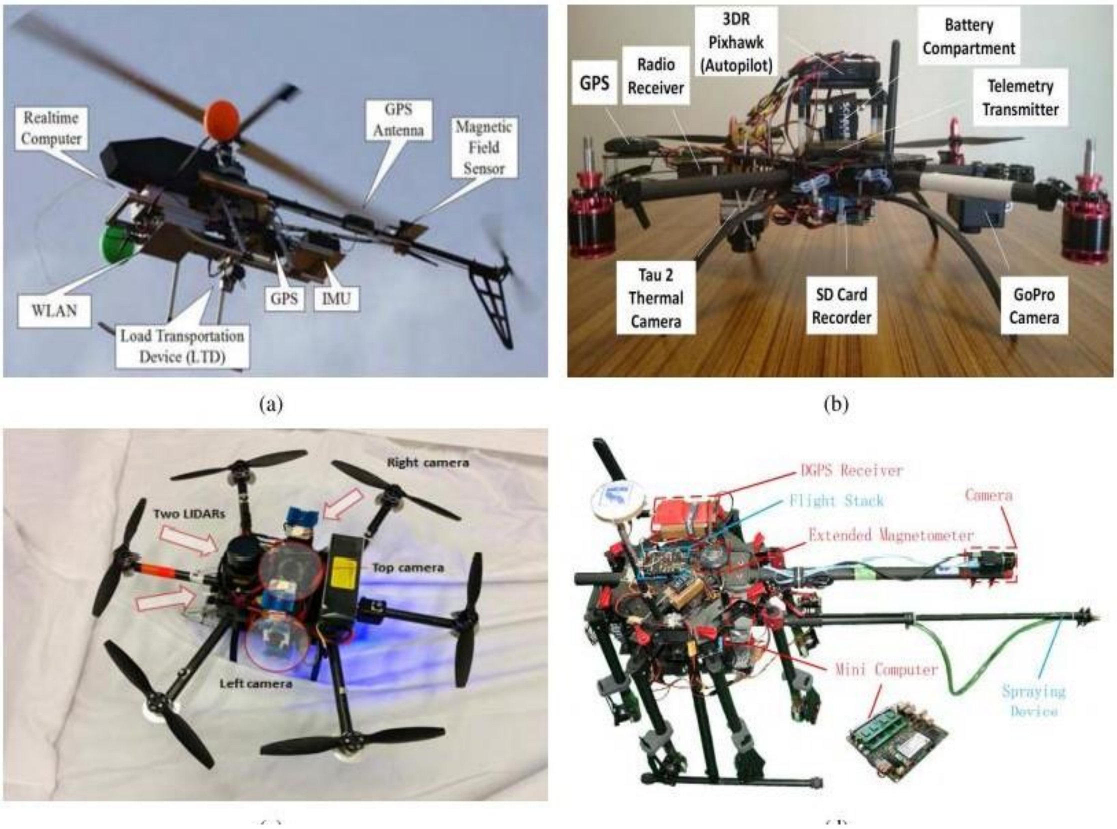


Figure 6. Multiple sensors attached to drones: (a) helicopter-type, (b) quadcopter, (c) hexacopter, and (d) octocopter (Kim *et al.*, 2019)

7.2. Drones Spraying in Rice Area

In agriculture, labour usage is critical, significantly when eliminating the rice field weeds. Extensive labour was needed to control weeds in the rice fields from plant growth until harvest time (Dilipkumar *et al.*, 2020). Drone technologies can improve the efficiency of chemical spraying in the agricultural industry, alleviate labour shortages in the sector, and increase crop output and performance (Talaviya *et al.*, 2020). Furthermore, using drones for herbicide spraying can reduce herbicide use and maximize efficiency (Kim *et al.*, 2019).

Comparison herbicide spraying using a mist blower, power sprayer and drone for agricultural application as in Table 4.

Table 4. Comparison herbicide spraying using a mist blower, power sprayer and drone for agricultural application

No	Items	Mist Blower	Power Sprayer	Drones
1	Tank Capacity	20 litres	1,000 litres	20 litres
2	Spraying volume per hectare	200 litres	300 litres	20 litres
3	Number of workers	1	4	1
4	Working hours per hectare	1 hour 40 minutes	30 minutes	15 minutes
5	Working hours per day	3 hours 30 minutes	4 hours	Up to 8 hours
6	Productivity	2 hectares	8 hectares	Up to 20 hectares

(Source: FELCRA Berhad, 2020)

The Integrated Weeds Management (IWM) strategies in rice cultivation must minimize the evolution of herbicide-resistant weeds (Rahman *et al.*, 2017). The cultural, mechanical, and chemical weed management solutions for different types of rice-establishing methods in different agro-ecological zones in rice-growing locations in Malaysia should be created and fine-tuned to fit farmers' individual demands and to prevent herbicide-resistant weed evolution (Rao *et al*., 2013). The safe use of herbicides should be popularized among the rice farmers. Drones and other remote sensing devices for surveillance and herbicide applications based on the presence or absence of weeds should be developed or improved for systemic monitoring and usage in site-specific weed management (Che' Ya, 2016).

Figure 7. DJI AGRAS T20 for herbicide spraying in paddy area (Sanyeong Agricultural Solutions)

7.3. Application of Drone with Sensor Technologies for Weed Detection

Hyperspectral imaging obtains images of continuous narrow wavebands. It generates the spectrum for each pixel in the image to identify weed species in the field (Su, 2020).

Hyperspectral imaging is capable of capturing objects in hundreds of narrow bands, producing detailed information and quantifying plant health, classifying the types of plants, weeds detection and plant vegetation based on spectral signature by the remote sensing satellite or aerial imaging (Adão *et al.*, 2017; Esposito *et al.*, 2021; Wendel & Underwood, 2017). Hyperspectral sensor technology such as hyperspectral thermal infrared with visible near-infrared (VNIR) and shortwave infrared (SWIR) reflectances are also used in water stress detection of the plant (Gerhards *et al.*, 2019).

The human eyes have a limitation and have vision capacity for a definite range from the electromagnetic spectrum from 400 to 700 nm (Singh *et al.*, 2020). Hyperspectral imaging contains several wavelength bands across a spectral range. It brings a colour dataset with helpful information with huge spatial resolution and thousands of pixel data per leaf (Gerhards *et al.*, 2019).

Weed management requires an integrated approach and new technologies for site-specific weed management (Huang *et al.*, 2016). Precision agriculture depends on combining technologies such as sensors machine learning to inform management to optimize productivity and reduce environmental impact (Esposito *et al.*, 2021). Combining drones with various sensors has become a standard tool in precision agriculture, such as RGB, multispectral, hyperspectral and thermal sensors. Figure 8 shows the UAV systems used in detecting weeds.

Figure 8. Example of UAV system used in detecting weeds (the pictures were captured by the author)

8. Sensor Technology for Sustainable Weed Management

Weed management requires an integrated approach and new technologies for site-specific weed management (Huang *et al.*, 2016). Precision agriculture depends on combining technologies such as sensors machine learning to informed management to optimize productivity and reduce environmental impact (Esposito *et al.*, 2021). Combining drones with Red-Green-Blue (RGB), multispectral and hyperspectral sensors has become a standard tool in precision agriculture. The three sensors are available depending on the spectral length, as depicted in Figure 9.

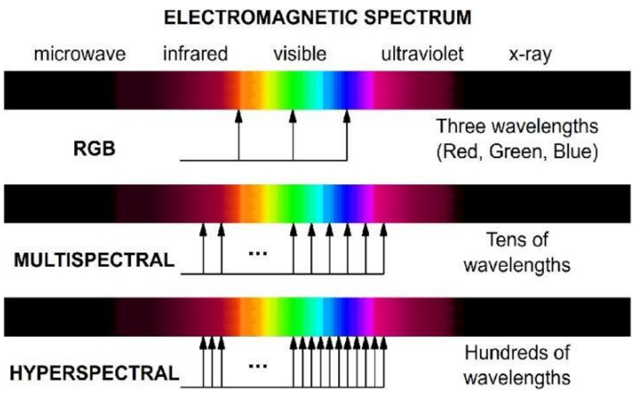


Figure 9. Comparison of electromagnetic spectrum for RGB, multispectral and hyperspectral wavelengths (Zabalza, 2015).

8.1. Red-Green-Blue (RGB) Sensor

Red-green-blue (RGB) imaging refers to the RGB camera set up with three colour filters to capture the scene image, a simulation of the standard way of the human eye to gain colour images (Su, 2020). RGB sensors are regularly used, and commercial cameras for weed presence and plant vegetation, such as determine vegetation indices (GRVI), excessive greenness (ExG), and greenness indices (GI) with high accuracy (Esposito *et al.*, 2021). The RGB sensor is low cost compared with a multispectral and hyperspectral sensor, but the early detection of the weeds is not applicable for this RGB sensor, but it can afford to detect the accurate location maps of weeds (Librán-Embid *et al.*, 2020).

According to Jere Kaivosoja (2020), the rice plant can differentiate between weeds using UAV integrated with RGB sensors (Kaivosoja *et al.*, 2021). Furthermore, an RGB image camera integrated with machine learning will interpret the image accurately to differentiate the weed species and the crop (Koot, 2014). Figure 10 compares RGB images and hyperspectral images in the field.

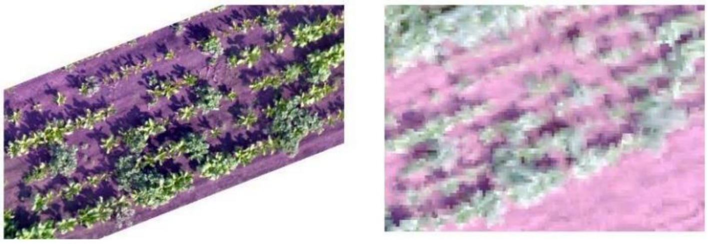


Figure 10. RGB image (left) and hyperspectral image (right) representing 450 nm as blue, 520nm as green and 650 nm as red (Koot, 2014).

8.2. Multispectral Sensors

Through spectrum vegetation indicators, multispectral sensors have the potential for weed detection, features, and insect damage (Librán-Embid *et al.*, 2020). Multispectral sensors are utilised for a broader range of vegetation indices computations because they can rely on a more significant number of radiometric bands and can be monitored for a more extended period than RGB sensors (Esposito *et al.*, 2021). Multispectral sensors are widely used with unmanned aerial vehicles (UAV) for data collection (Zheng *et al.*, 2018).

Multispectral and hyperspectral also used with thermal infrared remote sensing for crop water stress detection, combined with airborne applications and satellite concepts such as Sentinel 8, HiteSEM and HySPIRI/ SBG (Surface Biology and Geology) (Gerhards *et al.*, 2019). Multispectral sensor applications have a higher spectral resolution, and the imagery generally ranges from 5 to 12 bands compared with RGB sensors. (Adão *et al.*, 2017). Compared with hyperspectral sensors, hyperspectral imagery has higher resolution consisting of much higher band numbers, hundreds or thousands of them and arranged in a narrower bandwidth (5–20 nm) in Figure 11 (Adão *et al.*, 2017).

8.3. Hyperspectral Sensors

Hyperspectral imaging obtains images of continuous narrow wavebands. It generates the spectrum for each pixel in the image to identify weed species in the field (Su, 2020). Hyperspectral imaging is capable of capturing objects in hundreds of narrow bands, producing detailed information and quantifying plant health, classifying the types of plants, weeds detection and plant vegetation based on spectral signature by the remote sensing satellite or aerial imaging (Adão *et al.*, 2017; Esposito *et al.*, 2021; Wendel & Underwood, 2017). Hyperspectral sensor technology, such as hyperspectral thermal infrared with visible near-infrared (VNIR) and shortwave infrared reflectance (SWIR), is also used in the water stress detection of plants (Gerhards *et al.*, 2019).

Hyperspectral cameras, sensors, and machine learning increase crop quality and solve crop problems, such as detecting weeds in agricultural fields (Saha *et al.*, 2018). For example, utilizing supervised classification algorithms, weed identification using ground-based hyperspectral imaging in vegetable plants was successfully demonstrated with an accuracy of 80%. (Wendel & Underwood, 2016). Besides that, crop monitoring using a hyperspectral camera was successful, and hyperspectral data was given in the rice crop (Talaviya *et al.*, 2020).

9. Conclusions

Advances in production, information, transportation, and other areas have sparked new agricultural trends. Nowadays, incorporating drones and remote sensing UAVs into a crop monitoring assignment is becoming more common as technological advancements such as AI, including drones and remote sensing, have the potential to provide significant capacity in current and future agriculture applications (e.g. soil and field analysis, planting, crop spraying, crop monitoring, irrigation, and health assessment). AI in farm management has emerged as a robust, precise, cost-effective, and long-term solution for ensuring the agricultural sector's long-term viability in fulfilling food demand and supply. They are an instrument for studying land and crop conditions to collect data and information (particularly in crop/weed mapping using RGB, multispectral or hyperspectral remote sensing techniques) for further examination and decision-making. The application of AI technology in agriculture is highly convenient since it might alleviate labor shortages and eliminate human intervention in handling chemical pesticides. However, AI's engagement in the agricultural sector is still insignificant due to the higher cost of the equipment and the need for training before being deployed in the selected crop field (this circumstance focuses more on ordinary farmers in rural/isolated areas with low income). In general, AI practice in agriculture industries in Malaysia is still in its early stages. The technological advancements in AI will become a mainstream approach to revolutionizing agriculture for all stakeholders. Furthermore, the technology will support the agricultural industry and be a key for agriculture precision pillars (utilizing the correct method, place, time, and quantity).

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