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Review Article

Weed Management Using UAV and Remote Sensing in Malaysia Paddy Field: A Review

Zaid Ramli[1], Abdul Shukor Juraimi[1]*, Mst. Motmainna[1], Nik Norasma Che'Ya[2], Muhammad Huzaifah Mohd Roslim[3], Nisfariza Mohd Noor[4] and Anuar Ahmad[5]

[1]*Department of Crop Science, Faculty of Agriculture, Universiti Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia*
[2]*Department of Agriculture Technology, Faculty of Agriculture, Universiti Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia*
[3]*Department of Crop Science, Faculty of Agricultural and Forestry Sciences, Universiti Putra Malaysia Bintulu Sarawak Campus, 97008 Bintulu, Sarawak, Malaysia*
[4]*Department of Geography, Faculty of Arts and Social Sciences, Universiti Malaya, 50603 Kuala Lumpur, Malaysia*
[5]*Department of Geoinformation, Faculty of Built Environment & Surveying, Universiti Teknologi Malaysia, 81310 Johor Bahru, Johor, Malaysia*

ABSTRACT

Controlling weed infestation is pivotal to achieving the maximum yield in paddy fields. At a time ofexponential human population growth and depleting arable land mass, finding the solution to this problem is crucial. For a long time, herbicides have been the most favoured approach for weed control due to their efficacy and ease of application. However, adverse effects on the environment due to the excessive use of herbicides have prompted more cautious and effective herbicide usage. Many weed species tend to dominate the field, and the weed thrived in patches, rendering conventional broad herbicide spraying futile. Site-specific weed management (SSWM) consists of two strategies: weed mapping and selective herbicide application. Since its introduction into the agriculture sector, unmanned aerial vehicles (UAV) have become the platform of choice for carrying both the remote sensing system for weed mapping and the selective application of herbicide. Red-Green-Blue (RGB), multispectral and hyperspectral sensors on UAVs enable highly accurate weed mapping. In Malaysia, adopting this technology is

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E-mail addresses:
gs60804@student.upm.edu.my (Zaid Ramli)
ashukur@upm.edu.my (Abdul Shukor Juraimi)
motmainna@upm.edu.my (Mst. Motmainna)
niknorasma@upm.edu.my (Nik Norasma Che'Ya)
muhammadhuzaifah@upm.edu.my
(Muhammad Huzaifah Mohd Roslim)
nish@um.edu.my (Nisfariza Mohd Noor)
anuarahmad@utm.my (Anuar Ahmad)
*Corresponding author

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highly possible, given the nature of government-administrated rice cultivation. This review provides insight into the weed management practice using remote sensing techniques on UAV platforms with potential applications in Malaysia's paddy field. It also discusses the recent works on weed mapping with imaging remote sensing on a UAV platform.

Keywords: Hyperspectral remote sensing, paddy field, unmanned aerial vehicle (UAV), weed management

INTRODUCTION

As the global population is fast approaching the 8 billion mark, ensuring sufficient food supply has become a top priority for the world economies. Rice (*Oryza sativa* L), which feeds half of the world's population daily, accounts for 20% of the annual cereal grain production (Cai et al., 2022). In Asian countries, the role of rice as the staple food is more monumental as it supplies an astounding 70% of the daily calorie need (Rahman & Zhang, 2022). According to the latest data, global rice production stood at 508.7 million tons (Nawaz et al., 2022).

Rice cultivation is one of the main agriculture sectors in Malaysia, apart from rubber and oil palm plantations (Sulaiman et al., 2022). Approximately one million people are directly employed under the rice cultivation ecosystem. In terms of daily consumption, Malaysia's average rice consumption per capita in 2016 stood at 80 kilograms per person (Abidin et al., 2022). It is equivalent to 2.7 million tons of rice requirement per year. However, as of 2020, the local rice production was insufficient to fulfil the demand, with a total production of only 1.51 million tons. This situation has caused Malaysia to depend on rice imports from Thailand, Vietnam, and Pakistan to compensate for the deficit.

Numerous efforts have been undertaken to increase the production of rice. However, the infestation of weeds has proven to be the main biological hindrance in achieving the full rice yield potential, reducing cultivation profitability. Weeds compete for nutrients, light, space and moisture (Hasan, Ahmad-Hamdani et al., 2021). The extent of damage caused by weeds in rice cultivation depends on several factors. Among the most prominent are the weed species, their density in the planting area, and the competition duration. Meanwhile, the weed type and its persistence are determined by the type of crop, climate and season, date of sowing, and the cultivating methodology.

The loss of rice production in Malaysia is mainly due to the weedy rice (*Oryza sativa* f. *spontanea* Roshev) species infestation (Motmainna et al., 2021a; Mispan et al., 2019). Similar to other developing countries that produce rice, the shift from planting techniques to direct seeding methods in the last 35 years has amplified the weedy rice infestation. Though it is estimated that the rice loss in Malaysia is between 10–15%, the final extent of the loss can be much higher depending on the infestation level. At a high infestation level, defined by the presence of 21–30 weedy rice panicles per square meter, the loss can amount to 30% (Dilipkumar et al., 2021). In contrast, half of the cultivation can be lost once the infestation reaches a heavy level (≥31 panicles).

The control measures for weeds range from cultural, physical, biological and mechanical methods. However, chemical control involving the use of the herbicide has been preferred since it is the most effective and easiest to perform (Motmainna et al., 2021b; Hasan, Mokhtar et al., 2021). Herbicide is distinguished into different categories based on several criteria: its chemical family and formulation, mechanism of action, selectivity, site of uptake by the targeted weed, and based on its application times, whether it is pre-plant, pre-emergence or post-emergence (Monteiro & Santos, 2022). Unfortunately, excessive usage of herbicides causes harmful and detrimental environmental effects. Therefore, there is a need for a more sustainable weed management strategy.

Site-specific weed management (SSWM) is a method that enables accurate and site-specific application of herbicides on weeds of interest (Huang et al., 2020). It involves the process of weed mapping using specific remote sensing tools integrated into a suitable platform before the herbicide spraying process. Imaging remote sensors, namely Red-Green-Blue (RGB), multispectral, and hyperspectral, are the three different image sensors used widely in the agriculture industry (Roslim et al., 2021). Data gathered by the sensors is processed and interpreted by a suitable machine learning (ML) approach to produce a workable and precise weed mapping used for the site-specific herbicide application (Guo et al., 2022). Meanwhile, Unmanned Aerial Vehicles (UAVs) have gained attention among the available platforms for their brevity and precision (Monteiro & Santos, 2022). Through SSWM via remote sensing, the need for herbicide application can be determined based on the economic weed threshold, at which yield gain outweighed the overall cost of the chemical and its spraying operation. Numerous studies on cereals, maize, sugar, beat and peas have reported a 23–89% saving on herbicides (Gerhards et al., 2022). This paper reviews the weed problem involving rice plantations, with particular attention to weedy rice, and the solution via SSWM using remote sensing technology and the UAV platform for application in Malaysian rice fields.

RICE CULTIVATION IN MALAYSIA AND THE WEED PREDICAMENT

Rice is a seasonal crop with two cultivation cycles, with the first one beginning in April till September, followed by October and ending in March. A complete rice growth cycle lasts for 120-125 days. The cycle consists of three growth stages: (1) vegetative (1–41 days after planting), (2) reproductive (42–77 days), and (3) maturative (83–99 days). To boost rice production, Malaysia's government introduced a rice granary, arable land, with a centralised canal irrigation system that the federal government administrates (Ruzmi et al., 2021). To date, 12 rice granaries have been developed that cover a total area of 425,613 hectares. Most of the rice cultivation undertaken in Malaysia takes place in these granaries.

The manual rice transplanting method was used at the beginning of large-scale cultivation. Unfortunately, the shrinking workforce in the agriculture sector has made the transplanting method less practical (Alam et al., 2020). It is reported that the labour workforce has experienced a prolonged decline since the 1980s and eventually shrunk by 0.1% between 2010–2019 due to several factors, such as rapid urbanisation and an ageing farming population. The direct-seeded rice (DSR) technique was adopted to overcome this, in which the seed is sown directly into the soil (Shekhawat et al., 2020). Apart from requiring fewer workforces, it has become a method of choice since it is more rapid, has a low water requirement, and requires minimal mechanisation. It has also been reported that DSR experienced a 7–10 days early maturity (Nagargade et al., 2018). DSR has been adopted in Malaysia since the late 1980s (Ruzmi et al., 2021). In Asia, DSR is practised in 21% or 29 million hectares of the total cultivated area (Alam et al., 2020). Meanwhile, in Malaysia, due to the intensive adoption of mechanisation for rice cultivation, 90% of the total area is planted using DSR (Sulaiman et al., 2022).

In tropical Asian rice fields, yield loss caused by weeds is more significant than that caused by pathogens and insects. Rice is a naturally weak competitor and, under duress, will experience uneven flowering and non-uniform maturity. The severity of yield loss depends on the duration of competition with weed. Throughout the entire growth cycle, the first 41 days after sowing are the most critical, though keeping the cultivation free from weed for up to 70 days has been shown to guarantee a high yield (Shekhawat et al., 2020). If proper weed management is not practised during this critical period, yield loss could range from 15% to a complete loss (Busi et al., 2017). Major weed flora in DSR for the Asia region consists of 3 broad groups: grassy, sedges, and broadleaf (Table 1).

Table 1
Major weed species in Asia's rice field (Nagargade et al., 2018)

Grassy weeds	Sedges	Broadleaf weeds
Digitaria setigera Roth	*Cyperus iria* L.	*Commelina benghalensis* L.
Digitaria sanguinalis (L.) Scop.	*Cyperus difformis* L.	*Caesulia axillaris* Roxb.
Digitaria ciliaris (Retz.) Koeler	*Cyperus rotundus* L.	*Eclipta prostrata* (L.) L.
Echinochloa colona (L.) Link	*Fimbristylis miliacea* (L.) Vahl	*Ipomoea aquatica* Forssk.
Echinochloa crus-galli (L.) P. Beauv.		*Ludwigia octovalvis* (Jacq.) P. H. Raven
Eleusine indica (L.) Gaertn.		*Ludwigia adscendens* (L.) H. Hara
Ischaemum rugosum Salisb.		*Monochoria vaginalis* (Burm.f.) C. Presl

Table 1 *(Continue)*

Grassy weeds	Sedges	Broadleaf weeds
Leptochloa chinensis (L.) Nees		*Sphenoclea zeylanica* Gaertn.
O. sativa		
Paspalum conjugatum P. J.Bergius		

Despite its numerous advantages in advancing the rice cultivation sector, DSR has given rise to severe weed infestation worldwide. Due to prolonged and continuous DSR implementation, the original weed flora in Southeast Asia rice fields has shifted towards the more aggressive grassy and sedge weed species. The most notable species that has caused the most damage is the weedy rice, which belongs to the same genus and species as cultivated rice (Motmainna et al., 2021a). Severe weedy rice infestations have been reported in China, India, Bangladesh, Bhutan, Nepal, Sri Lanka, the Philippines, Vietnam, Thailand, Malaysia, and the USA. In Malaysia, weedy rice is known by its local name, *padi angin*, translated as wind rice, for its grains are often shattered by wind gusts (Motmainna et al., 2021c). The first case of weedy rice infestation was reported in 1988 in the Northwest Selangor Project rice field in Sekinchan (Mispan et al., 2019). It then spread to the rest of the rice granaries. In some of the granaries, an infestation rate of more than 50% of the total cultivated land has been reported. Weedy rice possessed numerous characteristics that made it possible for it to survive and thrive in the rice area. Morphologically, weedy rice is taller than cultivated rice, making it more efficient in capturing sunlight. It also has higher tillering when competing for space. The photosynthetic rate and the nitrogen uptake efficiency of weedy rice are also superior, depriving the cultivated rice of enough nutrients for growth. Higher stress tolerance is also associated with the weed plant (Motmainna et al., 2021d). The weedy rice seed has a faster germination rate and can stay dormant in the soil bed for a consecutively long period of up to 10 years.

Weed control is pivotal to ensure maximum yield and avoid crop destruction. Manual weed control, though effective, is not preferred on the commercial scale since it depends on a large labour workforce. Chemical control via herbicide is the most applied method in rice cultivation. Herbicide is a chemical substance formulated to pass through the plant's membrane surface and exerts toxic and lethal effects inside the cell (Hasan et al., 2022). Generally, there are two types of herbicides: (1) pre-emergence and (2) post-emergence with varying chemical active ingredients (Table 2). Pre-emergence is sprayed within three days following the seed sowing. As for the post-emergence herbicide, an early application takes place 10–12 days after sowing, while a late application is made 25–30 days after sowing.

Table 2
Commonly used herbicide in paddy fields based on the active ingredients (Hafeez-ur-Rehman et al., 2019; Shekhawat et al., 2020)

Pre-emergence	Trade name	Post-emergence	Trade name
Nitrofen	Tok E-25	Bispyribac sodium	Adora 10 SC
Butachlor	Machete	Pyrazosulfuron	Ojika
Pendimethalin	Stomp	Ethoxysulfuron	Sunrice
Thiobencarb	Bolero	Penoxsulam	Granite
Oxyflorfen	Goal	Glyphosate	Roundup
Oxadiazon	Ronstar	2,4-D	Weedar 64
Oxadiargyl	Topstar	Fenoxaprop	Acclaim Extra
Pretilachlor	Sofit	Azimsulfuron	Gulliver
Acetochlor	Harness	Propanil	Stamp F-34

Unfortunately, applying herbicides in agriculture is associated with variousdetrimental effects. It causes contamination to the soil surface, which, as a result, reduces soil microbial communities and earthworm populations. Consequently, the naturally occurring soil nutrient enrichment process is affected, and the overall soil biodiversity is altered. Herbicides can seep deep into the ground and contaminate the groundwater reservoir (Monteiro & Santos, 2022). The residue of the chemicals can also be traced in the food supply. Meanwhile, continuous application of similar herbicides on the same field site triggers weed flora shift and develops herbicide-resistance weeds (Motmainna et al., 2021e). The on-field growth pattern of the weed creates another challenge for an efficient application of the herbicide. Weed grows heterogeneously and is spread throughout the entire field in patches. Without proper weed control, the weed aggregates in the designated patches over time and eventually becomes dominant over the cultivated species. Furthermore, flat spraying, in which herbicide is sprayed indiscriminately on the entire field, contributes to the thriving of a specific weed flora on specific patches. Therefore, a more prudent way is required to achieve satisfactory control over the weed infestation via herbicide application.

SITE-SPECIFIC WEED MANAGEMENT WITH REMOTE SENSING AND UAV

A better chemical weed control strategy through herbicide application involves two strategies. The first is identifying and selecting the zones or patches inside the rice field that require herbicide spraying. Secondly, the herbicide is applied exclusively on the determined site. These strategies of weed identification and selective herbicide application are known as site-specific weed management (SSWM) (Eddy et al., 2014). Meanwhile, the economic weed threshold is the decision-making process that determines the necessary herbicide spraying. Herbicide is sprayed only when the expected yield increase following the herbicide treatment exceeds the overall cost of the herbicide application. SSWM eliminates unnecessary herbicide usage, lowers production costs, and reduces contamination related to herbicides being released into the environment (Eddy et al., 2014). Remote sensing imaging technologies used in agriculture are the Red-Green-Blue (RGB) sensor, multispectral and hyperspectral.

Meanwhile, UAVs are becoming the preferred platform for carrying imaging sensors. It offers flexibility in its flying program due to its swift and fast deployment, which shortens the planning-to-flight time (Roslim et al., 2021). However, there are limitations related to UAVs in terms of their limitedflight time and data processing speed (Huang, Reddy et al., 2018). Three operators are required to accomplish the surveying operation. First is a radio control pilot responsible for manually launching and landing the UAV and activating the flight path. The second ground station operator controls the UAV position, flying altitude, flight speed, wind speed, radio control signal quality and battery level. Finally, a third operator is a visual observer to assess possiblecollision and obstruction. When coupled with UAV, the surveying and documentation process consists of three phases: (1) pre-flight planning, (2) in-flight image acquisition, and (3) dataset extrapolation. Besides the surveying task, UAVs have alsobeen utilised for selective herbicide spraying. A specified herbicide is applied directly to the weed patch, and excessive chemical usage can be avoided using data feed based on the weed mapping. The overall SSWM process is depicted in Figure 1.

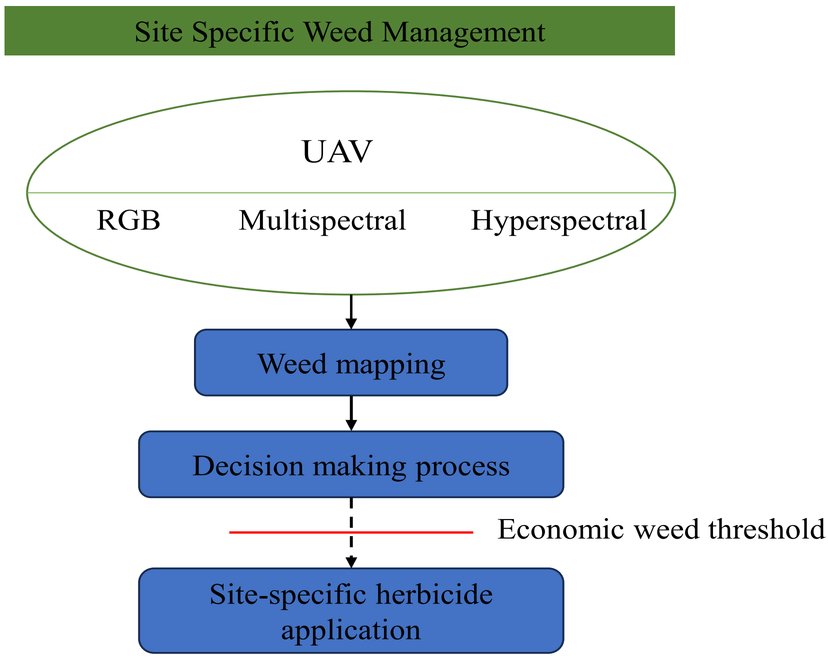

Figure 1. The overall process of site-specific weed management using herbicide via UAV and remote sensing

SSWM with remote sensing and UAV may solve the problem of weed infestation. However, the adoption rate of the technology for on-field applications is relatively slow. Economic feasibility, particularly the return on investment, is a critical factor that worsens the situation. There are costs associated with hardware and software procurement and data acquisition. In addition, a large land area of more than 500 hectares is required to make the technology economically feasible (Hunt & Daughtry, 2018). Other factors contributing to the low adoption rate are the farmer's age, educational background, and ownership status of the land.

AVAILABLE SENSORS FOR REMOTE SENSING

RGB Sensor

RGB is the most basic imaging remote sensing technology currently in use. A normal consumer camera with a red-green-blue visual spectrum can be readily utilised (Roslim et al., 2021). This type of sensor can measure vegetation indices (VI) such as the Greenness Index (GI), Excessive Greenness (EG), and Green/Red Vegetation Index (GRVI). RGB has the lowest cost and a shallow learning curve, making it easy fora novice to familiarise themselves and apprehend the process. Unlike the multispectral and hyperspectral sensors, RGB does not require radiometric calibration (Esposito et al., 2021). However, it is susceptible to low lighting conditions. Moreover, the ability of RGB to distinguish the weed from the cultivated plant depends on the degree of apparent and significant disparity between both plants (Zhang et al., 2019).

Before the flight, parameters such as the area coverage, flight altitude, topography, weather conditions and any related local regulations have to be determined (Esposito et al., 2021). During the flight, the operator needs to ensure that sufficient data is gathered to produce meaningful analysis. During the third phase, the individual images collected undergo rectification before being stitched together to generate a single image (orthomosaic) of the covered study area. The orthomosaic image can be represented by either the RGB values or the intended VI. In the broad agriculture application, the RGB sensor has been used to type the phenotypic features of plants such as the flower, fruit, branch, and trunk. In addition, information such as the leaf count, shape, colour, position and overall plant size has also been gathered via the RGB sensory process (Roslim et al., 2021). Meanwhile, the UAV-mounted RGB has been utilised for several purposes, such as producing the field map, identifying plants that experienced abiotic stress, and performing biomass estimation.

Multispectral Sensor

Multispectral sensor imagery ranges from 5–12 radiometric bands and can detect spectra in the visible spectrum and near-infrared region. Due to the additional bands, the range of VI that a multispectral sensor can monitor is expanded comparedto an RGB sensor (Esposito et al., 2021). Multispectral sensor requires radiometric calibration and atmospheric correction. Unlike the RGB sensor, which captures images, the multispectral sensor records the radiance from the field and converts it to digital numbers (Tu et al., 2018). The digital numbers are not exactly representative of the surface reflectance since the light illumination condition, and the consistency of the sensor influence the recorded numbers. Therefore, radiometric calibration is a prerequisite to obtaining consistent spectral information throughout the entire area of mapping. During the flight, the sensor will gather a high dataset volume. Input/output errors and missing data must be avoided to ensure sufficient and satisfactory data can be collected (Esposito et al., 2021). Finally, multiple images collected are rectified and georeferenced before they are stacked together to produce a single image with varying radiometric levels.

VI are algebraic combinations of several spectra at particular bands that indicate vegetation vigour and properties. Since the reflectance in the near-infrared region is more abundant than in the visible spectrum, many non-visible recognitions, such as early-stage plant disease and soil water content, can be harnessed (Esposito et al., 2021). Moreover, the accuracy of VI generated by the multispectral sensor is superior to the RGB sensor (Furukawa et al., 2021).

Hyperspectral Sensor

The hyperspectral sensor differs from the multispectral sensor in terms of the number of spectral bands and the bandwidth (Adão et al., 2017). The total number of spectral bands in hyperspectral imaging can extend to the thousands range with a bandwidth ranging from 5–20 nm, respectively. The enormous dataset gathered from the almost continuous spectra of the hyperspectral sensor enables a more in-depth and specific field characteristic compared to the multispectral sensor (Esposito et al., 2021). Processes and steps involved during the three phases of flight operation are almost similar to themultispectral sensor; however, they are more complex due to the greater complexity of the hyperspectral technology. Through hyperspectral imagery, narrowband VI, such as modified vegetation stress ratio (MVSR), transformed chlorophyll absorption ratio index (TCARI), and modified soil-adjusted vegetation index (MSAVI), can be calculated (Adão et al., 2017).

MACHINE LEARNING FOR WEED IDENTIFICATION

The initial step of a successful SSWM with remote sensing is detecting and recognizing weeds. The sensors' massive data must be processed to produce a workable and accurate weed mapping. Machine learning (ML), a subset of artificial intelligence, uses the current high computing performance to interpret the big data generated (Benos et al., 2021). ML involves a computer learning process based on data input without strict programming limitations (Liakos et al., 2018). The learning process occurs via various machine learning models and algorithms, and the performance of the ML process is validated using appropriate statistical measures.

ML is widely applied in various precision agriculture practices, including weed management. A typical ML takes place in four steps: data input, data pre-processing, model building, and generalisation (Sharma et al., 2021), as shown in Figure 2. The performance of ML improved over time with a gain in new data and experience, making it possible for the model and algorithm to come up with better and correct predictions (Domingos, 2012).

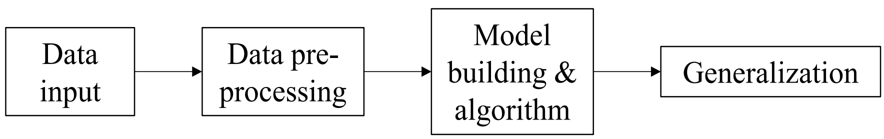

Figure 2. A general machine learning approach

RECENT PROGRESS ON WEED MAPPING VIA IMAGING REMOTE SENSING

The first part of a successful SSWM strategy is identifying and locating the weed infestation site and determining the necessity of selective herbicide application. Countless research on SSWM via remote sensing has been reported using multiple platforms. However, there is an increasing preference for UAVs as the platform of choice. Here, the latest works on this specific subject are compiled to present the current progress (Table 3). Only publications dated from 2018 are included in the compilation.

RGB sensors dominate the research realm regarding weed mapping using UAVs. Although a multispectral sensor is more stable and relatively unaffected by the surrounding conditions, it is more expensive than RGB. The RGB sensor's performance can be improved by modifying the camera. The near-infrared filter can be replaced with a red filter to make it more sensitive to the near-infrared spectrum (Maes & Steppe, 2019). Weed detection on the field can be achieved by employing two approaches. The first is detection via row crops, and the second is through spectral discrimination. In the first approach, the weed that flourishes between the row crops can be detected and identified through advanced algorithms analysis, most notably OBIA methodology that identifies spatially and spectrally similar objects through adjacent pixel grouping. Modified RGB cameras have been utilised for inter-row weed detection with high overall accuracy (Maes & Steppe, 2019). However, this approach is less effective in detecting weeds growing within the crop rows and for high-density crop cultivation such as wheat.

In the spectral discrimination approach, the weed is distinguished from the crop through disparity in the spectral signal (Maes & Steppe, 2019). Differential spectral-based discrimination allows for mapping multiple weeds (Eide et al., 2021). Multispectral and hyperspectral sensors work on this principle. Modified RGB cameras exhibited the same property; however, simultaneous detection of multiple weeds has yielded a low accuracy due to the limited number of spectral bands available. Several studies were done with multispectral, including on rice, where discrimination of barnyard and common purslane weeds was achieved with 94% accuracy (Stroppiana et al., 2018). However, only works on maize were reported for the hyperspectral sensor. One of the stumbling blocks hampering the progress of hyperspectral imagery-related research is the substantial cost of procuring the sensors. One unit of hyperspectral sensor would cost USD 175,000, compared to a multispectral sensor that costs just around USD 6,000. Moreover, accurate quantification of spectral indices of crops and weeds can be obtained through the cheaper multispectral sensor (Askari et al., 2019). An inherent limitation associated with the hyperspectral image is that it captures images at a low spatial and temporal resolution. This phenomenon occurs because the hyperspectral sensor captures images in a very narrow wavelength band, consequently limiting the number of photons able to imp the sensor per unit of time.

Furthermore, the instability of the sensor during the flight due to the vibrating nature of the UAV has further worsened the problem (Esposito et al., 2021). Regardless of the limitation, there has been a study to distinguish rice, weedy riceand barnyard grass based on spectral recognition using hyperspectral line-scanning images (Zhang et al., 2019). As a result, six wavelengths (415 nm, 561 nm, 687 nm, 705 nm, 735 nm, and 1007 nm) have been identified as the most important spectral features that enabled weedy rice and barnyard grass discrimination with 100% accuracy.

Table 3
Recent works on weed mapping with imaging remote sensing on a UAV platform

Type of sensor	Crops	Vegetation / spectral indices	Flying altitude (m)	Scopes and main findings	References
RGB	Rice	Not applicable	0.8 – 1.2	Weed (*Sagittaria trifolia* L.) identification. Weed mapping through the FCN method. Accuracy of 92.7%	Ma et al. (2019)
		ExG, ExR, GRVI, CIVE	20	Spatial weed distribution. Accuracy of 91.5%	Kawamura et al. (2021)
		Not applicable	6	Weed mapping through FCN. Accuracy of 88.3%	Huang et al. (2018b)
		Not applicable	10	Weed mapping comparison between OBIA and FCN methods. FCN performs better in terms of accuracy (83.3% vs 72.2%)	Huang et al. (2020)
		Not applicable	6	Weed (*L. chinensis* and *C. iria*) mapping via FCN. Accuracy of 94%	Huang, Lan et al. (2018)

Table 3 *(Continue)*

Type of sensor	Crops	Vegetation / spectral indices	Flying altitude (m)	Scopes and main findings	References
RGB	Oat	Not applicable	6	Real-time image processing onboard a UAV using the FCN method. Accuracy of 80.9%	Deng et al. (2020)
		Not applicable	10	Weed (*L. chinensis* and *C. iria*) mapping via FCN. Accuracy of 86%	Huang et al. (2018a)
		VARI, GLI, NGRDI, BI, CI, RI	10	Weed mapping. Accuracy of 87.1 – 89%	Gašparović et al. (2020)
	Wheat	ExG, ExR, ExGR	30	Weed mapping through the OBIA method. Overall accuracy of 83%	Mateen (2019)
		Not applicable	1–6	Individual classification of 4 types of weeds: *Matricaria chamomilla* L., *Papaver rhoeas* L., *Veronica hederifolia* L., *Viola arvensis* Murray., *Arvensis* using the DCNN method. Overall accuracy of 94%.	de Camargo et al. (2021)
		Not applicable	20	Weed against soybean mapping using the CNN method. Accuracy of 0.66	Sivakumar et al. (2020)
	Soybean	Not applicable	4	The existing imagery dataset was analysed using two established CNN methods and three custom CNNs. Custom 5-layer CNN has the highest accuracy at 97.7%, with the lowest latency and memory usage.	Razfar et al. (2022)
		Not applicable	4	Classification of soybean, grass and broadleaf weed. Overall accuracy of 99.4%	Haq (2021)
	Marigold	ExG, ExR, ExGR	20	Weed mapping and corresponding density on field infested with green bristlegrass, milkweed and sedge. The accuracy of weed mapping was 93.5%. The accuracy for weed density was 0.94.	Zou et al. (2021)

Table 3 *(Continue)*

Type of sensor	Crops	Vegetation / spectral indices	Flying altitude (m)	Scopes and main findings	References
RGB	Bean spinach	ExG	20	Weed mapping using a similar CNN method on two crops on different fields. Overall accuracy of 0.95	Bah et al. (2018)
	Sunflower & cotton	Not applicable	30 & 60	Early season weed mapping against two types of crops of different fields using a similar OBIA method. Accuracy of 81% (sunflowers) and 84% (cotton).	de Castro et al. (2018)
	Beet, parsley & spinach	Not applicable	20 & 30	Weed discrimination using the CNN method. Overall accuracy of 99%	Reedha et al. (2022)
	Pea & strawberry	Not applicable	2	Weed mapping using GAN method. Accuracy of 90% and comparable to the CNN method	Khan et al. (2021)
	Grassland	Not applicable	10	Mapping of *Rumex obtusifolius* L. from production grasslands via CNN method. 90% accuracy	Valente et al. (2019)
		Not applicable	10 & 20	Mapping of *R. obtusifolius* by combining OBIA and CNN method. Accuracy of 92.1%	Lam et al. (2021)
		Not applicable	25	Weed mapping through the CNN method. Overall accuracy of 87%	Pei et al. (2022)
	Maise	ExG	20	Weep mapping via OBIA with an accuracy of 0.945	Gao et al. (2018)
		Not applicable	Variable height	Weed mapping with augmented data via CNN method. Improved accuracy to 95.7% from 92.9%	Bullock et al. (2019)
	Tobacco	Not applicable	4	Weed mapping through 2-stage segmentation CNN. Improved accuracy from 0.76 (single stage segmentation) to 0.91 (two-stage)	Moazzam et al. (2023)
	Sesame	Not applicable	5	Mapping of weed using the newly established CNN method. Accuracy of 96.7%	Moazzam et al. (2022)
		Not applicable	120-240	Weed mapping through Mask R-CNN with augmented data. Accuracy of 0.803	Mini et al. (2020)

Table 3 *(Continue)*

Type of sensor	Crops	Vegetation / spectral indices	Flying altitude (m)	Scopes and main findings	References
		ExG	125-200	Comparison of weed mapping accuracy between machine learning and CNN method. CNN performed slightly better	Júnior et al. (2020)
	Wheat, maize & peanut	Not applicable	2	Mapping of three weeds: *Chenopodium album* L., *Humulus scandens* (Lour.) Merr., *Xanthium sibirium* Patrin ex Widder on three separate farmlands. Weed mapping was generated using the CNN method. Overall accuracy of 99.39% (RGB) and 99.53% (MS). Weed density accuracy was near the Ground truth values	Wang et al. (2022)
RGB & multispectral	Maise & sugar beet	NDVI (multispectral) & ExGR (RGB)	15 & 30	Mapping of creeping thistle and curled dock by combining data set from RGB and multispectral. Accuracy of 96% (maise) and 80% (sugar beetz)	Mink et al. (2018)
	Winter wheat	Not applicable	45	Large scale mapping of blackgrass from 31 fields (205 hectares) using the CNN method with an accuracy of above 0.9	Fraccaro et al. (2022)
RGB & multispectral	Maise & sugar beet	NDVI (multispectral) & ExGR (RGB)	15 & 30	Mapping of creeping thistle and curled dock by combining data set from RGB and multispectral. Accuracy of 96% (maise) and 80% (sugar beetz)	Mink et al. (2018)
	Winter wheat	Not applicable	45	Large scale mapping of blackgrass from 31 fields (205 hectares) using the CNN method with an accuracy of above 0.9	Fraccaro et al. (2022)
	Rice	SAVI, NDVI, RGRI, CVI, NDRE	70	Distinguishing *Echinochloa* spp. and *Portulaca oleracea* L.*)*.Overall accuracy of 94%	Stroppiana et al. (2018)
		NDVI	60	Weed mapping on cultivated rice field	Rosle et al. (2022)

Table 3 *(Continue)*

Type of sensor	Crops	Vegetation / spectral indices	Flying altitude (m)	Scopes and main findings	References
Multispectral	Maise	NDVI	50	Weed mapping of *C. album* and *Cirsium arvense* (L.) Scop. Accuracy of 80%	Louargant et al. (2017)
	Wheat	18 Vis were adopted, with the best performing being TGI	20	Mapping of *Alopecurus myosuroides* Huds. infecting wheat fields. Overall accuracy of 93%	Su et al. (2022)
	Soybean	NDVI	10	Detecting and mapping glyphosate resistance weeds of kochia, ragweed and amaranth after glyphosate application. The highest mapping accuracy scores were attained after 8 days of application. Respective accuracy score: kochia (0.752), ragweed (0.872), and amaranth (0.935)	Eide et al. (2021)
	Sorghum	Not applicable	10–38	Spectral data of sorghum and 6 types of weeds were collected with a handheld hyperspectral device. Data from identified bands were loaded into a multispectral sensor on a UAV for field surveying. Successful identification of sorghum, amaranth, liver seed grass, mallow weed, and nutgrass.	Che'ya et al. (2021)
	Green onion	Not applicable	4–5	Weed detection using CNN based on images curated from a video recording. Accuracy of 93.81%	Parico and Ahamed (2020)
	Sugar beet	NDVI	10	Production of high-resolution weed mapping on large area coverage using DNN. Accuracy of 0.782	Sa et al. (2018)
Hyperspectral	Maise	CNORM, GRDB, OSAVI	30	Maise field infested with 5 weeds. Analysis based on chlorophyll and carotenoid leaf behaviour. Introduction of two new spectral indices. Successful mapping of maise, Amaranthus and Cyperus-based on comparison with ground-based dry biomass and LAI index	Pignatti et al. (2019)
		CNORM, GRDB	30	Broad discrimination between weed and crop and dataset analysis using 3 methods. Amaranthus and Cyperus can be separated from maise using the CNORM/GRDB index and CNN methods. The quality of spectral images was compromised due to the instability of the UAV during the image-taking process	Casa et al. (2019)

SELECTIVE HERBICIDE SPRAYING USING UAV

The final strategy for a successful SSWM with herbicide is the ability to selectively applya specific herbicide on weed patches based on the information relayed by the weed mapping. UAV has been widely employed for this purpose. Generally, there are three types of UAVs: fixedwing, single rotor, and multiple rotors (Hanif et al., 2022). As for the multiple rotors UAV, the naming is based on the number of rotors: quadcopter (4 rotors), hexacopter (6 rotors) and octocopter (8 rotors). Multirotor is the most employed UAV in agricultural practices, with the quadcopter being the most preferred due to its greater stability (Rahman et al., 2021). UAVs allow selective herbicide spraying and expedite the application process, vital in large-scale cultivation where timely herbicide application is vital. The simultaneous deployment of multiple drones has also been explored to fulfil the timely herbicide spraying requirement (Chen et al., 2022). UAVs used in SSWM are equipped with numerous technological features, namely Global Positioning System (GPS), automatic path planning, high accuracy positioning, obstacle avoidance ability, real-time kinematics, automatic spraying system, and pulse width modulation system.

However, using UAV for herbicide spraying on the field is associated with drift and downwash airflow of the herbicide droplets associated with the vortex pulse created by the rotor.Consequently, uniform droplet deposition, the key to successful herbicide application, is not achieved (Hao et al., 2022). Studies have been done to minimise or eliminate the drift and downwash effects by studying the spraying parameters, such as the droplet size and the spraying rate (Chen et al., 2020). Apart from the spraying parameters, the droplet deposition is also influenced by several other factors: the UAV flight condition (altitude and speed), environmental factors (humidity, temperature, and wind speed), and the liquid properties (type and concentration) (Hao et al., 2022).

CONCLUSION AND FUTURE PROSPECT

Weed infestation will continue to become one of the biggest hurdles in achieving maximum crop production. SSWM is a formidable approach to solving the weed predicament. The induction of remote sensing and UAV as part of the SSWM strategy has offered a promising solution for the ongoing weed infestation. Implementing this technology in Malaysia's rice field can increase rice production and reduce its dependency on rice imports. Nevertheless, research related to this technology in Malaysia is either non-existent or insufficient to provide insight into its real-time application on local climate and conditions. Therefore, research is imperative to implementing thistechnology in Malaysia's paddy field.

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