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REVIEW

# Application of hyperspectral imaging to identify spectral signatures of grass weeds in rice at early stages: a review

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## KEYWORDS

Hyperspectral imaging, grassy weeds, rice crops, spectral signatures

## HIGHLIGHTS

- Grass weeds threaten rice crops by competing for resources, causing yield losses.
- Traditional weed control methods are labor-intensive, costly, and inefficient for large-scale rice production.
- Hyperspectral imaging captures detailed spectral data to distinguish weeds from crops.
- This technology boosts weed detection, reduces error, and offers a cost-effective solution.
- Hyperspectral imaging faces challenges like high cost, data complexity, and scalability.

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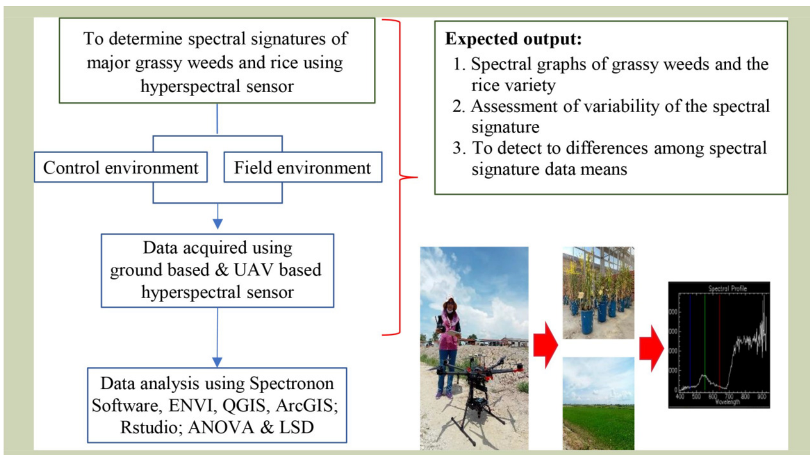
## GRAPHICAL ABSTRACT




## ABSTRACT

The productivity and yield of rice crops are continually threatened by various biotic and abiotic stressors, with weed infestations being a primary concern. Among the many types of weeds that challenge rice cultivation, grass weeds are particularly troublesome due to their competitive nature and fast growth, which can lead to significant yield losses if not managed effectively. Normally, the detection and control of grass weeds in rice fields have relied on labor-intensive visual methods, such as visual inspections and hand-weeding. These approaches are not only time-consuming but also prone to human error, making them inefficient and costly. In recent years, remote sensing, particularly hyperspectral imaging, has emerged as a promising technology for addressing this challenge. Hyperspectral imaging systems capture a vast amount of spectral information across numerous narrow wavelength bands, enabling the differentiation of various objects and materials based on their unique spectral signatures. The objective of this review was to examine the principles of hyperspectral imaging, its advantages over current methods, and the various techniques and approaches used in weed detection and classification. Also, this paper examines the challenges and limitations associated with this technology and identify potential areas for future research and development.



## 1 Introduction

Rice (*Oryza sativa*) is a strategic crop and the main cereal and staple food for over half of the global population, especially in Asia. However, the proliferation of weeds in rice fields poses a significant threat to crop yields and quality[1–3]. Rice production in Malaysia is decreasing due to agronomic problems, such as land preparation, limited crop rotation, pest and disease outbreaks, climate change, water management and weed problems[4,5]. In general, weeds present a major problem in rice cultivation when they compete for space, light and nutrients[6,7].

Weeds reduce rice productivity and grain quality, especially rice cultivating with direct seeding[8]. Rice fields usually intestate by three groups of weeds, such as grasses, forbs and sedges. Lately, grass weeds, particularly *Echinochloa crus-galli*, *Ischaemum rugosum* and *Leptochloa chinensis*, have become more serious direct-seeded problems than transplanting areas yield losses[7]. The grasses and other narrow-leafed weeds such as *Echinochloa colona*, *Echinochloa crus-galli* become the dominant weeds in rice fields, especially in the direct seeding of rice cv. MR219 during the main cropping season.

Indiscriminate weed management methods (both mechanical and chemical) are labor-intensive, time-consuming and often environmentally harmful[9]. Consequently, there is a growing need for precise and efficient weed detection and management technologies[10,11].

The reliance on visual observation for weed detection is a common practice due to its simplicity and lack of requirement for specialized equipment. However, this method is labor-intensive, time-consuming and often lacks accuracy, which can lead to inefficiencies and increased costs[12,13]. The physical similarities of weeds, such as grass weeds, and rice become a problem in the identification of weed populations especially at early growing stages. However, this approach is not practical in the field. Lately, unmanned aerial vehicles (UAVs) and multiple sensor attachments with drones are the latest development considered an eye in the sky has a huge potential to support agriculture in spatial data collection. The hyperspectral camera equipped with the drone can capture image on the ground to identify weeds species in the field[14].

According to Sulaiman et al.[15], identifying weeds grasses in rice crops is indeed a significant challenge, especially for large-scale using standard method However, recent research on large-scale identification of weeds in rice fields emphasizes using UAV-based remote sensing and machine learning for high accuracy in weed detection mapping[10,16]. For example, lightweight convolutional neural network deployed on UAVs have been effective in generating weed maps in rice fields, particularly during early growth stages when weeds are most competitive[17,18]. These models allow for real-time analysis and can create precise prescription maps for targeted herbicide application, optimizing input use and reducing environmental impact. This is a significant advancement over visual detection and enables faster, large scale assessment across rice fields[10,16,19].

Hyperspectral imaging (HSI), which captures and analyzes a wide range of spectral information across numerous contiguous bands, has emerged as a promising tool for weed detection in precision agriculture[20–22]. By leveraging the unique spectral signatures of plants, HSI enables the differentiation between crop and weed species[23]. Recent advances in machine learning and deep learning techniques have further enhanced the ability to process high-dimensional hyperspectral data, improving the accuracy of weed identification and classification[24–26].

UAVs provide an effective platform for deploying HSI technology in agricultural applications. UAVs offer the advantages of high spatial resolution, flexibility in data acquisition, and rapid coverage of large areas[27,28]. This combination of UAV-based HSI has shown significant potential for weed detection in rice fields, particularly in addressing challenges, such as varying environmental conditions, complex crop-canopy structures and spatial heterogeneity[20,29].

Studies in 2020–2024 have examined the integration of UAV-based HSI for precision agriculture, demonstrating its capability in identifying specific weed species, such as barnyard grass, weedy rice and other common infestations in paddies[30–32]. These studies have also highlighted the importance of developing robust data processing algorithms to address challenges related to high-dimensional spectral data and environmental variability. Despite these advances, practical implementation remains limited by several factors including the high cost of hyperspectral sensors, computational requirements and the need for real-time decision-making tools[9,10].

## 2 World rice production and challenges

World rice production in 2021 was about 787 Mt[15]. China leads by a significant margin, followed by India, Indonesia, Bangladesh and Vietnam, which also have substantial production figures. These five countries are responsible for over 85% of global rice production[33]. Other major rice-producing countries (in order of production) include Thailand, Myanmar, Philippines, Pakistan, Brazil, Cambodia, Japan and United States[15,34]. The rest of the countries listed show progressively smaller amounts of rice production. Factors affecting rice production include climatic conditions, the availability of arable land, access to water, agricultural practices, technological advancement in farming and government policies related to agriculture[35–38].

Rice production in Malaysia faces several challenges, including climate-related issues, policy constraints, and infrastructure limitations. In 2023, Malaysia’s rice production decreased by 4.7%–2.18 million metric tons, down from 2.28 million tons in 2022[39]. This decline was partly due to extreme weather conditions, such as droughts affecting key paddy-growing regions like Perak, Kedah, and Kelantan. Approximately 130,000 acres of paddy fields were impacted, leading to a significant reduction in yield This downward trend reflects the challenges faced by the rice industry in Malaysia. Factors influencing this trend include issues in agricultural practices, government policies and level of knowledge and training among farmers[39]. These trends highlight the need for focused interventions and improved agricultural practices to enhance rice productivity in Malaysia.

Also, rice production decreased because uncontrolled weed populations impacted establishment especially and other establishment is an early stage growth. For example, in direct-seeded rice, the narrow-leafed weeds, such as *E. crus-galli*, become dominant in the rice planting competing impacting establishment of rice especially from 21 to 40 days after seeding[40]. According to Chauhan & Abugho[41], increasing the rice seeding rate can greatly reduce the growth and seed production of *E. crus-galli* in direct-seeded rice systems, but other weed management strategies are needed for complete control. Also, weedy grasses can became hosts for certain biotic stressors, such as insect pests, rodents and plant pathogens[42].

## 3 Impact of grass weeds infestation in rice fields

Several types of grass weeds can be problematic in rice fields. The specific types of grass weeds can vary depending on the geographical location, climate and management practices[43]. However, some common grass weeds in rice fields are given in Table 1.

Grass weeds, such as *Echinochloa* and *Leptochloa* spp., can cause 20%–100% losses in rice[47,48]. Grass weeds are the predominant group of weeds in rice fields, followed by sedges and broadleaf weeds. Grass weed is particularly in rainfed environments, and its germination is greater at higher temperatures and favored by zero-till systems. Weeds also block drainage and irrigation systems in the fields[45]. Also, grass weeds, such as *E. crus-galli,* compete for nutrients in rice fields. In the early stages, grass weeds absorb the nutrients need for the growth of rice, especially nitrogen in direct-seeded rice[49].

Several studies have found that one of the most significant impacts of weed infestation is a reduction in yield[50–52]. Weeds can drastically reduce the number of grains per plant and the weight of each grain. In severe cases, weed infestation can lead to yield losses of over 50%. In addition to quantity, the quality of the rice grains can also be affected by the infestation of weeds[53]. Currently, effective weed control can provide a 95% weed-free crop[54]. Weeds can take over the field if they are not prevented from spreading during the vegetative stage, which will leave the crop without enough space, light or nutrients to grow and develop. Weeds can lead to poor grain-fill, and affect the appearance and quality of the harvested rice, which is likely

**Table 1 Grass weeds species in Asian rice field**

| Scientific name | Common name | Lifecycle |
|---|---|---|
| *Brachiaria mutica* (Forssk.) Stapf | Para grass, buffalo grass | Perennial |
| *Chloris barbata* Sw. | Swollen fingergrass, purpletop chloris | Perennial |
| *Cynodon dactylon* (L.) Pers. | Bermuda grass | Perennial |
| *Dactyloctenium aegyptium* (L.) Willd. | Egyptian crowfoot grass | Annual |
| *Digitaria adscendens* (Kunth) Henrard | Southern crabgrass, tropical finger-grass | Prostrate short-lived perennial |
| *Echinochloa colona* (L.) Link | Jungle rice, awnless barnyard grass | Annual |
| *Echinochloa crus-galli* (L.) P. Beauv. | Common barnyard grass | Annual |
| *Eleusine indica* (L.) Gaertn. | Crowfootgrass, goosegrass | Prostrate to ascending annual grass |
| *Ischaemum rugosum* Salisb. | Wrinkle duck beak, saromacca grass | Annual |
| *Leersia hexandra* Sw. | Southern cutgrass, clubhead cutgrass | Annual |
| *Leptochloa chinensis* (L.) Nees | Red sprangletop, Asian sprangletop, Chinese sprangletop | Perennial/Annual |
| *Oryza sativa* f. *spontanea* Roshev. | Weedy rice | Perennial |
| *Paspalum conjugatum* P.J. Bergius | Carabo grass, hilo grass | Perennial |
| *Paspalum scrobiculatum* L. | Kodo millet | Perennial |
| *Paspalum vaginatum* Sw. | Biscuit grass, saltwatercoucch | Perennial |
| *Rhynchelytrum repens* (Willd.) C.E. Hubb. | Natal grass, natal red top | Annual |

Note: Sources from Rao et al.[44], Zimdahl[45], and Saad et al.[46].

reduce its market value. Additionally, weeds can harbor pests and diseases that can transfer to rice plants[55]. There are several reports that weeds not only affect plant health but also increase the cost of production due to the need for additional pest and disease control measures[56–58].

Effective weed management is crucial in rice cultivation. This can include the use of pre-emergent and post-emergent herbicides, proper water management (as some weeds are less competitive in flooded conditions), use of competitive rice cultivars, and regular monitoring and manual removal of weeds. Integrated weed management strategies, combining cultural, mechanical and chemical methods are often the most effective in controlling weed infestation and minimizing its impact on rice growth and yield.

## 4 Importance of weeds detection in the early stages of rice production

The maturity period of rice plants depends on the cultivar and environmental conditions. Generally, the maturity period for most rice plants ranges from 100 to 120 days after sowing (Fig. 1)[10]. Farmers need to be aware of the specific maturity period for the rice cultivar they are using to plan the harvest and other agricultural activities accordingly. They go through three developmental phases: vegetative, reproductive and maturing. During these phases, weed management is crucial to ensuring a higher yield through meticulous planning and timely implementation. For rice plants to progress through each stage and produce a good yield, they also require an adequate quantity of nutrients, water, and sunlight[60].

Rice establishment impacted by weeds have reduced tillering. Application of herbicide in this stage must adhere to the guidelines to avoid injury to the rice due to the development of toxic compounds in membrane cells of the rice[61]. Using the herbicide in uncontrolled amounts, times and locations will interfere with the rice growth and yield, and the environment. However, early detection of weeds can improve weed management and reduce herbicide use by up to 50%[62].

Early detection of weeds in establishing rice crops is crucial to ensure to identification of the type of weeds and make the correct choice of herbicide. Also, during crop establishment, the weeds will compete for light and space. According to Juraimi[63], The major grass weeds such as *E. crus-galli*, *I. rugosum* and *L. chinensis* have similar characteristics to rice at early growing stage and it is challenging to distinguish between the rice plants within 10–30 days of growing (Fig. 2).

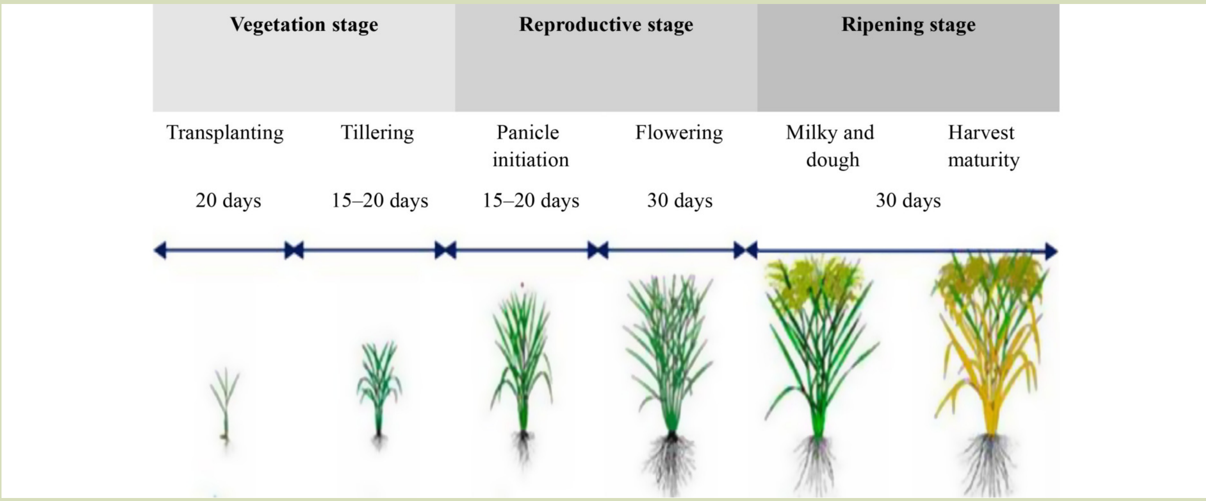



**Fig. 1** Growth stages of rice crop. Data from Chauhan[59].

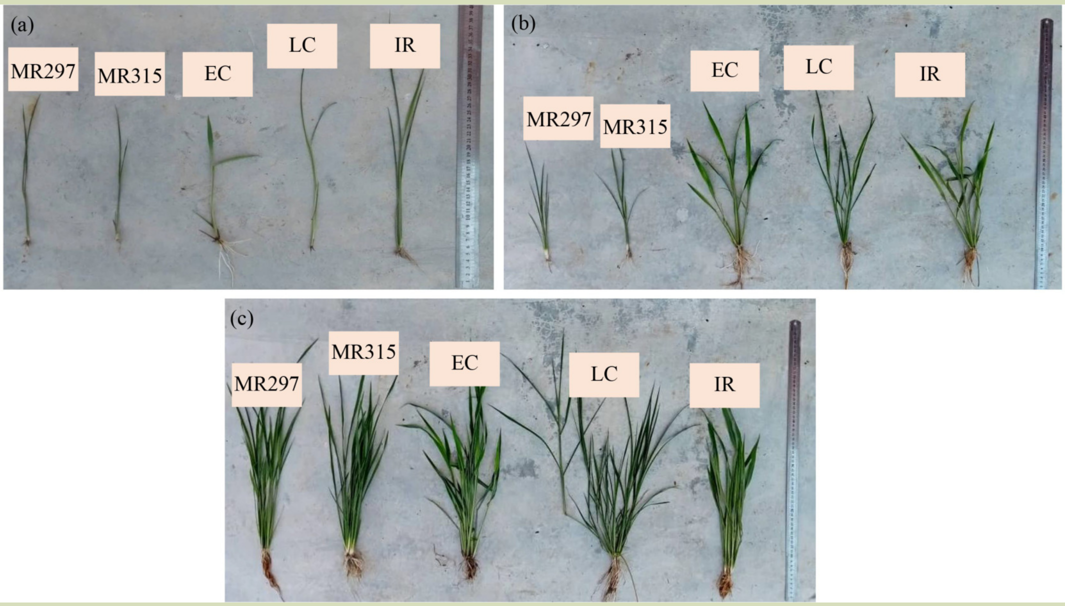



**Fig. 2** Different characteristics of rice cultivars MR297 and MR315, and major grass weeds, *Echinochloa crus-galli*, *Ischaemum rugosum* and *Leptochloa chinensis* at different growth stages. (a) 10 days after planting; (b) 20 days after planting; (c) 30 days after planting.

## 5 Hyperspectral imaging in weed detection

Hyperspectral imaging is a powerful technology that captures and process information from across the electromagnetic spectrum, providing detailed information about the composition and characteristics of objects and materials. It combines spectroscopy with imaging capability, allowing for the identification of objects and materials by analyzing their unique spectral signatures. For weed detection, hyperspectral imaging can be a powerful tool because it allows for the identification of plants based on their unique spectral signatures[64]. Hyperspectral imaging can accurately classify crops and weeds based on their distinct spectral characteristics, making it useful for weed detection[65]. A combination of spectral imaging and texture analysis can effectively discriminate crop and weed plants, with a mean discrimination accuracy of 90% between all plant species[66]. The distinct spectral signature of each plant species can indeed be exploited for accurate and efficient weed detection using hyperspectral imaging and machine learning technologies. Several studies have demonstrated the potential of hyperspectral imaging combined with machine learning for weed detection and discrimination[16,20,67,68].

Hyperspectral imaging has been successfully applied in a wide range of agricultural applications, including estimating crop biochemical and biophysical properties, monitoring crop health, detecting diseases, assessing soil quality and analyzing the growth process in real-time[69]. The technology offers a non-destructive alternative to slow direct sampling and grading of produce, enabling precise and targeted use of resources such as irrigation, fertilizer and pesticides. Hyperspectral imaging has been effectively used for weed detection in agriculture. Hyperspectral imaging data can be used to identify invasive and weed species in agroecosystems, with the combination of the Vis derivative index, chlorophyll content index and pigment-specific normalized difference being effective[70]. By capturing unique spectral signatures of various weed species, hyperspectral imaging, combined with machine learning algorithms, enables fast and accurate discrimination of weeds in crops. This technology has also been applied to identify and map weeds in fields. They are allowing for the automated discrimination of different weeds species, such as grass and broadleaf weeds, with high accuracy. There is evidence to suggest that substantially more studies have been published and research in the recent decade about hyperspectral imaging in weeds detection in Table 2.

Identification of weeds based on hyperspectral imaging and machine learning can be automated[17,18]. The ability of hyperspectral imaging to detect unique spectral signatures of a diverse group of weed species including grass and broadleaf weeds, with the aim of providing alternatives to standard control approaches. Hyperspectral imaging and machine learning can accurately identify weeds pastures with a range of overall accuracy of 70%–100%, with 89% accuracy in multilayer perception method[17]. Another study focused on identification of *Amaranthus palmeri* using hyperspectral imaging and machine learning technologies in soybean fields, highlighting the potential of this combination for real-time weed detection[18,77].

Hyperspectral sensors can be used for weed detection in agriculture. These sensors can capture hyperspectral images of crops and detect unique spectral signatures of weed species, including grass and broadleaf weeds[20]. Hyperspectral sensors can record hundreds to thousands of narrow radiometric bands, usually in visible and infrared ranges, and the choice of number and radiometric range of bands is critical[10]. The hyperspectral images can be captured by UAVs or ground-based sensors. Machine learning algorithms can be used to analyze the hyperspectral images and identify weed patches with useable accuracy depending on flying altitude, camera resolution and UAV used[11]. Some of the benefits of hyperspectral and multispectral imaging are that these technologies are low cost, give consistent results, simple to use, allow for rapid assessments, non-destructive, highly accurate and have a broad range of applications. There are several types of hyperspectral sensor that can be used for weed detection in

**Table 2 Studies on about hyperspectral imaging for weed detection**

| Weeds | Research focused | Reference |
|---|---|---|
| *Solanum nigrum* L. | Assessed the efficacy of hyperspectral imaging in weed management by providing early warning of glyphosate and glufosinate effects | [71] |
| *Orobanche cumana* Wallr. | Assessed the viability of using hyperspectral imaging to detect parasitism early on by tracking variations in the spectra of the host plants | [72] |
| *Mikania micrantha* Kunth | Savitzky-Golay, principal component analysis and support vector machine are the three classifiers used in hyperspectral imaging for the identification of the invasive plant, *Mikania micrantha* | [73] |
| *Jacobaea vulgaris* Gaertn. | Described three typical pasture weed species in New Zealand based on their proximate spectral reflectance measurements. | [74] |
| *Echinochloa crus-galli* P. Beauv., *Oryza sativa* f. *spontanea* | Hyperspectral imaging techniques used to create a classification model with significant spectral properties to identify these two weeds and rice | [7] |
| *Portulaca oleracea* L., *Euphorbia humifusa* Willd. and *Eleusine indica* Gaertn. | Field imaging spectrometer device used to distinguish between crops and weeds | [75] |
| *Bassia scoparia* A.J. Scott | Early identification, prompt action and site-specific control of herbicide resistance | [55] |
| *Avena sterilis* L., *Phalaris* spp. | Hand-held field spectroradiometer used to identify spectral characteristics in the visible and near-infrared windows to distinguish wheat, wild oats and canary grass at their final phenological stages | [76] |

agriculture. Some common types of hyperspectral sensor are given in Table 3.

Also, a study conducted about hyperspectral imaging data and machine learning to explore the possibility of fast, accurate and automated discrimination of weeds in pastures, demonstrating the potential to rapid and efficient weed identification in agricultural settings[20,42]. Additionally, a project aimed at early detection of herbicide-resistant weeds in a soybean field used hyperspectral imaging and machine learning algorithms to accurate and quickly map different weeds species, focusing on herbicide-resistant versus herbicide-susceptible weed biotypes[17,80]. These studies collectively illustrate the successful application of hyperspectral imaging and machine learning for weeds detection, leveraging the distinct spectral fingerprints of plant species to enable accurate and efficient discrimination of weeds in agricultural environments. Hyperspectral imaging and machine learning techniques successfully detect weeds in agricultural environments, improving the effectiveness of pesticides and increasing the economic benefits of agricultural products. Hyperspectral imaging and machine learning can accurately detect weeds in agricultural environments, with recognition performance varying between 31% and 98% for different weed species[81,82].

## 6 Spectral signature of weeds from hyperspectral imaging

A spectral signature represents the reflection, emission, or absorption of energy at each wavelength across the electromagnetic spectrum and is used for remote material identification by comparing the collected signature to the reference library. The spectral signature of an object is the characteristics of its surface transmission, absorption and reflection of electromagnetic radiation, represented in to dimensional space in the form of spectral curves. According to Martin et al.[83], hyperspectral remote sensing can effectively discriminate grass weeds in winter cereal crop, but only during first phenological stages due to different fraction cover crops and weeds. Hyperspectral camera images can accurately detect green weeds in a green lettuce crop, but accuracy is below the target value of 90% and the best hyperspectral narrow bands can achieve over 90% accuracy in classifying vegetation and agricultural crops, providing a 9% to 43% increase in accuracy compared to Landsat[14].

Also, hyperspectral measurements GEOSCAN drone trial with Gamaya hyperspectral camera provide accurate remote monitoring of weeds, enabling precise identification and management of weeds[84]. Additionally, the weighted support vector machine with six spectral features selected by SPA can achieve 100%, 100% and 92% recognition rates for *E. crus-galli*, weedy rice and rice in rice crop, potentially designing a customized optical sensor for weed management[7]. Hyperspectral imaging can effectively differentiate barley genotypes for resistance to powdery mildew by linking gene expression and spectral reflectance properties, enabling non-invasive phenotyping of plant resistance.

**Table 3 Types of hyperspectral sensors on aircraft and satellite**

| Sensor model | Platform/Brand | Spectral bands | Number of bands |
|---|---|---|---|
| Airborne Hyperspectral Sensors | Aircraft/UAVs | Visible-near infrared (VNIR) | |
| AisaFENIX | Specim | 380–2500 nm (adjustable) | 224 or 448 |
| Headwall Nano-Hyperspec | Headwall | 400–1000 nm | 270–324 |
| HySpex Eagle | NEO/Specim | 400–2500 nm | Up to 1600 |
| Satellite Hyperspectral Sensors | Satellite Brands | Shortwave infrared (SWIR) | |
| EO-1 Hyperion | NASA | 355–2575 nm | 242 |
| WorldView-3 | DigitalGlobe | 400–2500 nm | 8 SWIR + 8 VNIR |
| Sentinel-2 (MSI; multi-spectral instrument) | ESA | 443–2190 nm | 13 VNIR + 3 SWIR |
| Spectral Image Sensors | Various Platforms | Thermal infrared | |
| Specim IQ | Specim | 400–1000 nm (VNIR), 1000–2500 nm (SWIR) | 204 or 224 |
| Resonon Pika II | Resonon | 400–1000 nm (VNIR), 1000–2500 nm (SWIR) | 224 or 324 |
| Cubert UHD | Cubert | 450–850 nm | Up to 11 |

Note: Sources from Sulaiman et al.[15], Esposito et al.[11], Abdulridha et al.[78], and Pepe et al.[79].

Hyperspectral imaging UAVs are drones equipped with sensors can capture high resolution imagery at various wavelengths. UAVs equipped with hyperspectral sensor can capture high resolution imagery at various wavelengths for environmental sensing application such as agriculture, vegetation, geology and pollution monitoring. Lightweight hyperspectral cameras in UAVs can provide comparable and differentiable spectral signatures for agricultural applications compared to field spectrometers[85].

The hyperspectral imaging system for UAVs demonstrates good image quality and stable spectral position, with potential applications in airborne remote sensing applications. For example, the hyperspectral camera provided the best accuracy for UAV-based spectral monitoring in vineyards, with a photoelectric range between 1.0% and 13.6%, highlighting the importance of reference panels for radiometric calibration[86]. Other example, UAV-Rikola images show potential for accurate grassland classification, but low precision and accuracy due to unstable lighting conditions and near-infrared sensor malfunctions hinder further development. According to Pott et al.[87], red and near-infrared spectral bands are more accurate than other bands in distinguishing weeds from non-target plants before cash crop planting, supporting site-specific weed management.

A spectral signature is the ratio of reflected radiation energy and is dependent on wavelength $Er(\lambda)$ to incident radiation energy $Et(\lambda)$ on an object. Every substance on the surface of the earth has unique spectral reflectance values. The color and tone of an object in a picture are directly correlated with its reflectivity[88]. The wavelength of light reflected from the surface an object can be used to characterize its color and spectral reflectance, which is an average of its individually determined wavelengths helps to set it apart from other objects[89]. The reflectance $\rho(\lambda)$ value varies with the wavelength and terrain features and can be expressed as:

$$\rho(\lambda) = \frac{Er(\lambda)}{Et(\lambda)} \times 100 \tag{1}$$

## 7 Spectral characteristic of vegetation in different spectral regions

Green light is significant for biological systems, impacting biochemistry, physiology and structure, with a variety of photoreceptors and mechanisms leading to responses[90]. The electromagnetic spectrum responses of green, healthy vegetation between the green visible and near-infrared wavelengths. This was supported by Junior et al.[91] and Avery[92], who noted that healthy green vegetation mostly reflects green light (wavelength 545–565 nm) and interacts with near-infrared light (wavelength 841–876 nm).

Spectral characteristics of vegetation are influenced by various factors such as leaf properties and ecophysiology, and can be analyzed using remote sensing parameters, spectral indices and optimized algorithms to extract biophysical information, map vegetation cover types and monitor vegetation health[93]. For their case study of the Barton Peninsula, Chi et al.[94] developed a spectral library for 16 common plant species and decayed moss in Antarctica, highlighting the importance of shortwave-infrared wavelengths in identifying vegetation. Also, spectral characteristics of vegetation can be discriminated using Near-infrared and red waveband regions. Additionally, the spectral reflectance of vegetation can be detected in full spectrum, the visible, near-infrared and shortwave-infrared regions[77]. The spectral reflectance of vegetation can be detected in the following three major regions of electromagnetic spectrum as shown in Table 4.

Studying the spectral reflectance curve of green vegetation is a very effective way to learn about its traits and features. Chlorophyll is a significant feature in plants photosynthesis process[95–97].The amount of chlorophyll in a green vegetation can be ascertained by analyzing the reflectance curve of the plant because chlorophyll is present in green vegetation, it has a very low reflectance in the visible range[20].

Leaves appear green to human eye because they reflect most of the green light (centered on 533 nm) and absorb 70%–90% of incident visible radiation, particularly in blue and red wavelengths (centered on 450 nm and 670 nm respectively)[98]. Leaf spectra can improve predictions of spectral signatures of plants by influencing foliar pigment class, concentration, anatomical and ultrastructural plant cell characteristics. The spectral signature of a plant canopy is influenced by leaf optical properties, canopy geometry, soil reflectance and foliar properties, but incorporating leaf spectra can improve predictions.

According to the structural properties of the leaf, most of the energy is transmitted and reflected, creating a near-infrared plateau[99,100]. The red edge, which is used to identify plant stress, is the abrupt increase in reflectance between the red and near-infrared region[91]. The soil and leaf water absorption dominates the middle-infrared region (1.3–2.5 μm), particularly at 1.4 and 1.9 μm, with reflectance rising as leaf liquid water content falls.

Table 4 Three major regions of electromagnetic spectrum[77]

| Spectral region | Major controlling factor | Spectral characteristic |
|---|---|---|
| Visible region (400–700 nm) | Plant pigmentation | Healthy vegetation exhibits low reflectance and minimal transmittance overall due to high absorption of chlorophyll<br>Healthy vegetation appears green because chlorophyll greatly absorbs blue light (450 nm) and red light (670 nm) and powerfully reflects green light<br>As a result, vegetation has a distinct spectral signature that helps us differentiate it from inanimate objects |
| Near infrared (700–1350 nm) | Internal leaf structure | The cell structure is responsible for the high transmittance and reflectance as well as the extremely low absorption<br>High transmittance and reflectance as well as very low absorption are seen as a result of the cell structure |
| Shortwave/middle infrared (1350–2500 nm) | *In vivo* water Content | The cell structure results in high transmittance and reflectance and very little absorption<br>Due to the cell structure, there is very minimal absorption and high transmittance and reflectance |

## 8 Issues and challenges using hyperspectral imaging for weed detection

Hyperspectral imaging has been proposed as a potentially useful technique for weed detection due to its ability to capture unique spectral signatures and morphological features of weeds. However, there are several challenges and issues associated with using hyperspectral imaging for weed detection. According to Sulaiman et al.[15], collecting hyperspectral image data are relatively simple but obtaining image-like label information can be quite challenging in data acquisition. This is support by Patel et al.[101], who noted that obtaining image-like label information for hyperspectral images can be challenging due to a smaller number of labeled samples available. Hyperspectral imaging technology collects information from hundreds of images using remotely sensed devices but obtaining image-like label information can be challenging[19]. Also, obtaining labeled data for hyperspectral image classification is expensive and time-consuming, making it difficult to design classifiers based on limited samples[102]. This is particularly relevant when dealing with weeds, as they can be difficult to identify and classify.

Also, hyperspectral images often suffer from high redundancy of adjacent spectra and insufficient feature information extraction, leading to improved accuracy through spatial and spectral information integration in image processing[103]. The proposed hyperspectral image compression system reduces spectral and spatial redundancies while preserving spectral information, achieving high signal-to-noise ratio system and classification accuracy[104]. Additionally, feature selection algorithms can reduce redundancy in hyperspectral image and improve classification accuracy and computational time[105]. Common feature extraction methods in hyperspectral imaging face severe limitations due to their mathematical design and lack of physical consideration for imaging conditions[106]. However, Jing et al.[107], proposed an algorithm for hyperspectral image classification using spectral correlation improves efficiency in pure pixel extraction and classification, with a classification accuracy of 86%.

The development of accurate and reliable classification models for weeds detection is essential for practical applications. In some studies, machine learning algorithms, such as partial least squares-discriminant analysis, support vector machine and multilayer perceptron have been used for weeds detection[108–110]. However, the new classification method based on deep structure and least squares support vector machine has suitable performance in solving large-scale data set classification problems.

In some cases, the limitation using hyperspectral imaging is the presence of shadows in hyperspectral images can affect the accuracy of weeds detection[20]. This can be particularly problematic when scanning is performed in the field, where shadows may be more prevalent. Zhao et al.[111] achieved shadow compensation using an unsupervised cycle-consistent adversarial network that enhanced object detection and material classification in an hyperspectral imaging application. Also, hyperspectral image classification can be improved by using wavelengths near blue light and the longest near infrared available in the camera range.

In another case, enhancing the spatial-spectral attention in hyperspectral imaging can improve the identification of weeds[17]. However, this requires advanced techniques and may add complexity to the data processing and analysis. The spectral-spatial-self-attention network improves the classification of hyperspectral images, potentially aiding in the identification of weeds. Also, this approach improves hyperspectral image classification accuracy by suppressing the effects of interfering pixels. Another study indicate that a spectral and spatial residual attention network improve hyperspectral imaging, and light detection and ranging fusion and classification for land cover classification[112].

Despite these challenges, hyperspectral imaging has shown promise detecting weeds in various crops such as rice fields and other crops. Hyperspectral imaging has shown potential in detecting weeds in various crops, such as rice fields, by classifying plants according to their species using differences in spectral characteristics. Hyperspectral imaging has shown promise in detecting weeds in various crops, such as rice fields, using algorithms and modeling for weeds discrimination analysis[20].

Addressing these challenges requires ongoing research and technological advancements to improve data processing capabilities, enhance spectral signature discrimination and optimize the integration of hyperspectral imaging with other technologies. Additionally, it will be essential to overcome these challenges in order to promote the effective use of hyperspectral imaging for weeds detection in agriculture. Further research and development in this area could lead to more accurate and efficient methods for weed detection and management.

## 9 How artificial intelligence influences hyperspectral imaging of weeds

Artificial intelligence (AI) has revolutionized hyperspectral imaging by significantly enhancing its capability to identify and manage weeds in agricultural settings. Hyperspectral imaging captures data across numerous wavelengths, offering detailed spectral information for each pixel in an image. However, analyzing this vast amount of data manually is impractical. AI algorithms, particularly machine learning and deep learning, have addressed this challenge by enabling automated and precise analysis[113].

**Improved data analysis and pattern recognition:** Machine learning models can process complex hyperspectral data sets to extract meaningful patterns by identifying subtle differences in the spectral signatures of weeds and crops, these models achieve species-level accuracy in weed identification[25]. For example, a study in wheat fields demonstrated that convolutional neural network-based models could differentiate between wheat and common weeds, such as wild oats, with over 95% accuracy[114].

**Real-time processing and decision-making:** AI facilitates real-time processing of hyperspectral data, enabling timely weed detection and management. This real-time capability ensures that weed infestations are addressed promptly, minimizing competition between weeds and crops[115]. The integration of edge computing with AI allows on-site processing, reducing the dependency on centralized systems and enhancing decision-making efficiency.

**Adaptive learning systems:** Adaptive learning systems, powered by AI, improve their accuracy over time by learning from new field data. These systems incorporate feedback from changing environmental conditions, crop cultivars and weed species, ensuring consistent performance across diverse agricultural contexts[116]. This adaptability is critical in managing weeds effectively in dynamic field conditions.

**Reduction in manual errors:** Standard methods of weed identification often rely on visual scouting, which is time-consuming and prone to human error. AI-driven hyperspectral imaging minimizes these errors by automating the detection process, leading to more reliable results[114].

**Enhanced integration with precision agriculture:** AI-powered hyperspectral imaging aligns seamlessly with precision agriculture practices, enabling site-specific weed management, such that it can be used to optimize the use of resources such as herbicides, reducing environmental impact and enhancing sustainability[117].

According to Singh and Patel[117], a practical application of AI-driven hyperspectral imaging in rice farming involved managing barnyard grass in South East Asia. Researchers collected spectral data from rice fields using hyperspectral sensors mounted on drones. AI algorithms analyzed the data to distinguish barnyard grass from rice plants based on their unique spectral signatures. The system identified weed-infested areas with over 90% accuracy, allowing for site-specific herbicide application. As a result, farmers experienced a 20% increase in rice[117]. This example illustrates how AI and hyperspectral imaging synergizes to enhance both productivity and sustainability in rice cultivation. In summary, the synergy between AI and hyperspectral imaging transforms weed management into a precise, efficient and sustainable process. As the technology continues to evolve, its applications are expected to expand, offering even greater benefits to modern agriculture.

Hyperspectral imaging, combined with AI, offers significant economic advantages for weed identification in rice fields compared to current practices. Current methods, such as visual scouting or standard imaging, are labor-intensive, time-consuming and often prone to human error[117]. Hyperspectral imaging automates the weed detection process, reducing labor costs and improving the accuracy of weed identification.

Additionally, according to Wang et al.[115] precise weed detection enables targeted herbicide application, lowering chemical use and associated costs. This approach not only reduces expenditures on herbicides but also minimizes crop damage and environmental pollution. Hyperspectral imaging contributes to higher rice yields and overall profitability by improving weed management efficiency[115].

For example, a pilot study in India demonstrated that implementing hyperspectral imaging in rice paddies reduced weed management costs by 25% and increased yields by 15% compared to established methods[15]. These economic benefits highlight the potential for widespread adoption. The initial investment in hyperspectral imaging technology can be offset by long-term savings in labor, chemical inputs and yield improvements. Studies have shown that adopting advanced imaging techniques can lead to a significant return on investment, making it a cost-effective solution for modern rice farming[114,117].

## 10 Conclusions

Hyperspectral imaging has shown great potential for weed detection and management in agriculture. The technology uses a wide range of wavelengths across the electromagnetic spectrum, allowing for detailed and specific information about the composition of objects in the scene. Also, hyperspectral imaging provides a higher spectral resolution compared to the established imaging techniques, enabling better discrimination between different plant species and weed types. Additionally, the detailed spectral information allows for the identification of subtle differences in plant characteristics such as color, texture and biochemical composition. Hyperspectral sensors can detect weeds at early stages of growth, allowing for timely intervention and more effective weed control strategies. Early detection also helps in minimizing the competition between weeds and crops for resources, leading to improved crop yields.

In precision weed management, the high spatial and spectral resolution of hyperspectral images enables precision weeds management. Farmers can apply herbicides more selecting specific weed species and reducing the overall use of chemicals, which is environmentally friendly and cost-effective. Also, hyperspectral imaging can be integrated with automated system systems and robotics for real-time weeds detection and treatment such as hyperspectral UAV-based. This integration facilitates the development of smart systems that operate efficiently and reduce the need for manual labor. Advanced data analysis techniques, including machine learning algorithms, can be applied to hyperspectral data for accurate and automated weed identification. The development of robust models enhances the reliability and efficiency of weed detection systems.

However, challenges in terms of costs and the complexity of hyperspectral imaging systems need to be addressed for widespread adoption. Therefore, calibration and standardization are crucial to ensure the accuracy and consistency of hyperspectral data across different environments. Additionally, precision weed management using hyperspectral imaging contributes to environmentally sustainable agriculture by reducing the environmental impact of herbicides and promoting more targeted interventions.

Finally, for future directions, ongoing research and development in hyperspectral imaging technology will likely lead to more affordable and user-friendly systems, fostering broader adoption in agriculture. Integration with other technologies such as UAVs and satellite imagery, may further enhance the capabilities of hyperspectral weed detection. In conclusion, hyperspectral imaging offers a powerful tool for weed detection and management in agriculture, providing farmers with valuable information for decision-making and contributing to more sustainable and efficient farming practices.

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**Compliance with ethics guidelines**

Syarifah Noor Irma Suryani Syd Ahmad, Abdul Shukor Juraimi, Nik Norasma Che'Ya, Ahmad Suhaizi Mat Su, Muhammad Huzaifah Mohd Roslim, Nisfariza Mohd Noor, and Mst. Motmainna declare that they have no conflicts of interest or financial conflicts to disclose. This article does not contain any studies with human or animal subjects performed by any of the authors.

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