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Review Article

Detection of Sedge Weeds Infestation in Wetland Rice Cultivation Using Hyperspectral Images and Artificial Intelligence: A Review

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ABSTRACT

Sedge is one type of weed that can infest the rice field, as well as broadleaf and grasses. If sedges are not appropriately controlled, severe yield loss will occur due to increased competition with cultivated rice for light, space, nutrients, and water. Both sedges and grasses are monocots and have similar narrowed leaf characteristics, but most sedge stems have triangular prismatic shapes in cross sections, which differ them from grasses. Event sedges and grasses differ in morphology, but differentiating them in rice fields is challenging due to the large rice field area and high green color similarity. In addition, climate change makes it more challenging as the distribution of sedge weed infestation is influenced by surrounding abiotic factors, which lead to changes in weed control management. With advanced drone technology, agriculture officers or scientists can save time and labor in distributing weed surveys in rice fields. Using hyperspectral sensors on drones can increase classification

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accuracy and differentiation between weed species. The spectral signature of sedge weed species captured by the hyperspectral drone can generate weed maps in rice fields to give the sedge percentage distribution and location of sedge patch growth. Researchers can propose proper countermeasures to control the sedge weed problem with this information. This review summarizes the advances in our understanding of the hyperspectral reflectance of weedy sedges in rice fields. It also discusses how they interact with climate change and phenological stages to predict sedge invasions.

Keywords: Climate change, drone, internet of things (IoT), rice, smart farming, weed

INTRODUCTION

Rice is one of the world's most important food sources and Malaysia's third most important crop (Hakim et al., 2010). However, weed, a well-known rice pest, is causing significant crop loss in rice cultivation worldwide (Hakim et al., 2013). Moreover, the shift of abundance and dominance of sedges and other weeds, which are dynamic (Juraimi et al., 2013), make the invasion prediction for the coming season more challenging.

Several sedge weeds in rice fields and the most invasive species in Malaysia are *Fimbristylis miliacea*, *Cyperus iria*, *Cyperus difformis*, and *Scirpus grossus* (Hakim et al., 2013). Each weed species had its unique spectral signature captured by a hyperspectral camera (Norasma et al., 2020). However, the changing climate, including rainfall, daylight hours, temperature, relative humidity, and the duration of the drought season (Alam et al., 2014), may alter the levels of weed invasion and crop-weed competition, which is prone to benefit the weeds due to their better adaptation (Iqbal et al., 2020). These changes will also influence the spectral reading (Arias et al., 2021) and need to be considered when capturing the spectrum for sedge weed identification. Moreover, the phenological changes of a species will also result in different spectrum measurements as the biochemical bio-physical traits occur when a sedge weed enters a new growth stage, for example, before and after the emission of floral tassel (Voss et al., 2021).

Smart farming utilizes Unmanned Aerial Vehicles (UAVs) and Internet of Things (IoT) paradigms to achieve sustainable agriculture. IoT technology will reduce the inherent climate impact with the combination of UAVs by enabling real-time reactions toward sedge infestations in rice fields (Islam et al., 2021). The weed infestation rate in rice fields can be determined by comparing spectral signature information with ground data, which can later be recorded in a smartphone app to help farmers combat weed problems (Norasma et al., 2020). Using a spectral signature enables faster detection of weeds in the field than the traditional method, which takes longer and requires more time to cover the entire rice field (Norasma et al., 2020). Hyperspectral remote sensing, or spectroscopy, can identify differences between species in agricultural and non-agricultural environments (Basinger et al., 2020).

With hundreds of spectral bands, hyperspectral simultaneously captures spectral and spatial information (Zhang et al., 2019). Numerous airborne hyperspectral scanning instruments have been developed by embedding the sensor in a UAV (Lillesand et al., 2015). UAVs, also known as drones, can provide high-quality images and are a more economical solution than human-crewed aircraft or satellite images (Radoglou-Grammatikis et al., 2020). In summary, a UAV is an uncrewed aircraft controlled remotely by an operator and can carry a variety of cameras, including hyperspectral cameras, to capture aerial photos. Insecticide and fertilizer prospecting and spraying, seed sowing, weed recognition, fertility testing, mapping, and crop forecasting are UAV applications in agriculture (Islam et al., 2021).

Forecasting sedge infestations based on the changing climate can create an early and real-time warning system for farmers to take suitable actions. However, there is insufficient information about the spectral information of sedges growing in rice fields. Predictive modeling using artificial intelligence (AI) technology with deep learning is also required to analyze spectral differences. Changes in sedge morphology at different phenological stages and climate conditions may result in variations in spectral reflectance. Therefore, hyperspectral information should also be considered in a few phenological phases of sedges under climate variation, including atmospheric temperature, relative humidity, flooding conditions, and soil salinity. This review aims to focus on the role of the hyperspectral sensor, which is a part of remote sensing (RS), in distinguishing weedy sedges in rice fields and discuss the potential of spectral reflectance responses in different climatic settings and phenological stages, which can potentially be used to create a forecasting system for sedge infestation in the rice cultivation industry.

WETLAND RICE CULTIVATION

Due to vast low and flat land availability, farmers hugely plant rice in Malaysia’s northern and eastern sides, especially in Kedah and Kelantan (Norasma et al., 2020). In addition to low and flat land, wetland rice cultivation requires a steady and abundant water supply throughout its life cycle (Norasma et al., 2020; Simma et al., 2017). One study categorized rice land ecosystems into four types: irrigated, rainfed lowland, upland, and deep-water (Khush, 1997). With higher area coverage, irrigated rice is the primary technique farmers use and has higher production than other rice areas (Anwar et al., 2011; Juraimi et al., 2013). Approximately 57% of rice production in Peninsular Malaysia is obtained from ten granary areas with extensive irrigation and drainage facilities (Dilipkumar et al., 2020). However, fluctuations in rainfall patterns worldwide due to the changing climate have threatened water resources and rice productivity (Simma et al., 2017). Maintaining sustainable rice production is crucial because it supplies the primary food (Rahim et al., 2017). Rice production also contributes to farmers’ social and economic aspects by providing jobs and opportunities (Rahim et al., 2017). A study also predicted a faster increase in rice demand than in its production in most countries (Ismail & Abdullah, 2020). The Malaysian government imported rice from different countries to compensate for the shortage in domestic output supply (Dilipkumar et al., 2020). Moreover, a lack of weed management can reduce rice production (Norasma et al., 2020).

WEED PROBLEM

Weed problems have existed throughout history (Ismail & Abdullah, 2020; Juraimi et al., 2009). Weeds are unwanted plants that grow in the same area as the crops (Ahmad-Hamdani et al., 2021; Hasan, Hasan, Mokhtar et al., 2021; Motmainna et al., 2021a; Uddin et al., 2010). Weed infestation devastates crop production and overall yield (Hakim et al., 2014; Mondal et al., 2011). They interfere with the field activities of rice production systems during the crop-growing season. Besides, the existing practice uses uniform application of herbicides, resulting in high environmental degradation and low crop field productivity (Motmainna et al., 2021b; Motmainna et al., 2021c; Pantazi et al., 2016). In most situations, weeds take advantage of disturbed areas, allowing them to use the available resources effectively and grow abundantly (Ismail & Abdullah, 2020). They are very competitive with crops for all resources, such as nutrients, light, space, and water, negatively affecting crop production (Motmainna et al., 2021d; Galal & Shehata, 2015). In addition to the competition mentioned above, weeds can exert allelopathic effects on rice plants by reducing plant height and dry weight, which inhibit crop growth and development (Ismail & Siddique, 2012; Motmainna et al., 2021e).

Malaysia's average rice yield loss is between 10% and 35%, with grass, broad-leaved weed, and sedge yield losses of 41%, 28%, and 10%, respectively (Juraimi et al., 2013). Yield losses rely primarily on climate, weed species and density, rice varieties, growth rate, management practices, and rice ecosystems (Juraimi et al., 2013). Weed control is more critical in direct-seeded systems than transplanted systems because weeds can emerge simultaneously or before rice plants, leading to a severe competition problem (Begum et al., 2006; Galal & Shehata, 2015).

The weed flora population in rice fields usually consists of different types of grasses, sedges, and broadleaf weeds (Ismail & Abdullah, 2020). After grasses, sedges rank second in abundance among primary rice weeds (Yaduraju & Mishra, 2008). However, in the main season, sedges were the most common weeds, followed by broad-leaved weeds and grasses (Juraimi et al., 2010). During the early season, grasses are typically the most dominant, whereas sedges and broadleaf weeds dominate later (Yaduraju & Mishra, 2008)

SEDGES WEEDS INFESTATION

Many taxa in the Cyperaceae (sedges) family are highly aggressive weeds and are the main or even dominant components of many plant communities, especially in wetland areas (Simpson et al., 2011). The Cyperaceae family is a monocotyledonous angiosperm containing 106 genera and 5387 species (Govaerts & Simpson, 2007). They are classified as Poales and have a superficial resemblance to the Poaceae (grasses) (Simpson et al., 2011). They have a global distribution and are absent from the Antarctic continent. They can be found at altitudes ranging from sea level to 5000 m in the Himalayas and various habitats, including high Arctic tundra, tropical woodland, and seasonally wet grasslands (Simpson et al., 2011).

Sedges are similar to grasses but have three leaves and typically have triangular stems that do not have nodes and internodes (Yaduraju & Mishra, 2008). Most sedges thrive in relatively wet habitats, such as rice fields (Ueno, 2001), and some are adapted to pH 4 and below (Gabriel et al., 1986). Similar to grasses and broad-leaved weeds, sedges drastically reduce the number of productive tillers due to weedy competition (Juraimi et al., 2010). Sedges are generally more competitive with underground components, such as rhizomes, tubers, or roots (Yaduraju & Mishra, 2008).

Fimbristylis miliacea, *Cyperus iria*, *Cyperus difformis*, and *Scirpus grossus* (Table 1) were the four most abundant sedges in 32 separate rice fields in the coastal zone of Sebarang Perak in West Malaysia (Hakim et al., 2013). Although *Cyperus rotundus* is not an aggressively infesting rice-planting area in Malaysia, it is one of Asia's four most important sedge weeds (Issahaku et al., 2021). In the coastal rice-growing area of Kedah, *C. rotundus* was only 10 % in terms of frequency compared to *F. milliacea*, *C. iria*, *C. difformis*, and *S. grossus* with 67.50, 60.00, 60.00, and 52.50 %, respectively (Hakim et al., 2010). Figure 1 shows examples of pictures of sedge weeds in Asia that are inflorescent.

Table 1
Details on the top four sedges infest Malaysia rice fields

Scientific name	Common name		Life cycle	Propagation	Chemical Control
	English	Malay			
Fimbristylis miliacea (L.) Vahl (C4)	Lesser fimbry	Rumput tahi kerbau	Annual/ Perennial	Seed	2,4-D, bensulfuron-methyl, ethoxysulfuron, pyrazosulfuron-ethyl
Cyperus iria L. (C4)	Grasshopper's cyperus	Para/Rusiga anak emas	Annual	Seed	2,4-D, bispyribac sodium, ethoxysulfuron, pyrazosulfuron-ethyl
Cyperus difformis L. (C3)	Small-flowered umbrella plant	Para	Annual	Seed	2,4-D, bensulfuron-methyl, cyclosulfamuron, ethoxysulfuron, pyrazosulfuron-ethyl
Scirpus grossus L. f. (C3)	Creater club-rush	Menderong	Perennial	Stolon, tuber, seed	2,4-D, bensulfuron-methyl, ethoxysulfuron

Source: Hakim et al., 2013; Bruhl & Wilson, 2007; Man et al., 2018

(a) (b) (c) (d)

Figure 1. Pictures of the three most troublesome sedge rice weeds in Asia (Adapted from Caton et al., 2010): (a) *Cyperus iria* is a tufted weed with a dense flower ranging from yellowish-brown to greenish; (b) The umbellate and dense globose or ovoid inflorescence of *Cyperus difformis*; (c) *Fimbristylis miliacea* is a slender, tufted herb with a reddish-brown flower that is compound; and (d) *Scirpus grossus* is a rhizomatous perennial herb, with small spikelets flower that is often brown or greenish brown

The composition of the weed population in rice cultivation varies depending on a range of factors, including cultural practices (either transplanting or direct seeding), rice variety, location, water and soil management, methods of weed control, the current weed flora population, and climatic conditions (Ismail & Abdullah, 2020). For example, sedge and grass weeds are more dominant in transplanting than in broadleaved practices, but broadleaved weeds are the most prevalent in wet seedling practices (Aqilah et al., 2012). Weed populations are also distinct between conventional and organic rice farming systems (Kurniadie et al., 2019).

Integrated control techniques, including indirect and direct control methods, have been implemented to manage weed infestation in rice fields (Azmi et al., 2000). Clean and weed-free seeds, tilling, land preparation, water management, cultivar selection, and crop rotation are examples of indirect controls. Manual weeding and chemical applications are examples of direct controls. Flooding is the most prevalent method of weed control in irrigated rice fields, such as annual sedges, which suppresses young weed seedling germination and growth using standing water at a height of at least 5 cm above the ground at the early stage of planting (Rodenburg et al., 2011).

CHANGING CLIMATE ON RICE AND SEDGE WEEDS

Agriculture is highly reliant on climate (Alam et al., 2014). In addition to agronomics and genetics, climate change affects crop yield and productivity in the long run (Stuecker et al., 2018). This exogenous force has been shown to reduce the impact of genetics (Bell et al., 1995). According to Alam et al. (2014), variations in climatic conditions have significantly impacted crops in Malaysia. They also stated that human actions have caused most modern climate change. Climate change has various effects on agriculture, which vary by region, time, and crop type (Alam et al., 2014).

According to a study, the influence of climate on rice production varies significantly by region and is strongly seasonally modulated (Stuecker et al., 2018). Climate conditions, such as rainfall, daylight hours, temperature, relative humidity, and the duration of the drought season, have caused crop production to vary from season to season (Alam et al., 2014). A previous study found that variations in soil moisture significantly affect rice production (Stuecker et al., 2018). Although temperature variability is of little importance, they also suggested that temperatures might be regularly exceeded by the end of the century if warming continues unabated, limiting rice production.

As the climate changes, the levels of weed invasion and crop-weed competition are likely to be altered (Jinger et al., 2017). This alteration is prone to benefit weeds, as many have been resistant to climate change and have better adaptation (Iqbal et al., 2020). Although the number of C4 species was estimated to range from 27% to 34% of all Cyperaceae species, there is a high potential for C4 sedge weeds to spread and wreak havoc on agricultural systems, especially in temperate regions (Simpson et al., 2011). C4 species, including *F. milliacea* and *C. iria* (Issahaku et al., 2021), are anticipated to have more advantages under water stress, high temperatures, and high light intensity conditions (Simpson et al., 2011). These advantages result in better adaptation of C4 weeds to hot and drier climates (Rodenburg et al., 2011) over C3 plants, including rice (Jinger et al., 2017). In addition, *C. rotundus* is considered the world's worst weed, and it has the ability to expand its distribution significantly (Simpson et al., 2011).

While it is well-acknowledged that climate change affects long-term interactions between crops and weeds, the degree of this impact is unclear (Ramesh et al., 2017). Despite its widespread infestation, little climate change research on Cyperaceae has been conducted (Simpson et al., 2011). Seasonal forecasting will likely become more critical to provide the information needed to guide agricultural management and prevent the compounding effects of abiotic variability and stress (Stuecker et al., 2018).

Detecting weeds in the early season is a first and critical step; introducing precision farming methods can also effectively manage weed problems while minimizing operational costs and environmental pollution (Chlingaryan et al., 2018; Torres-Sánchez et al., 2015). Considering the diversity of weed problems, no single control method, whether cultural, manual, mechanical, or chemical, would be sufficient to provide season-long weed control in all situations. An integrated weed management system as part of an integrated crop management system would be a practical, economical, and eco-friendly approach to managing weedy rice sedges (Yaduraju & Mishra, 2008).

INTERNET OF THINGS (IOT)

The dynamic changes in weed infestation, including sedges caused by the changing climate in rice fields, will result in more challenging control methods by farmers. Researchers and farmers can employ several strategies related to AI to monitor weedy pests regularly during and after rice production to prevent further damage (Bhoi et al., 2021). A real-time monitoring system that can precisely determine the severity of the current weed infestation can help farmers take appropriate and quick actions. Moreover, a prediction model to forecast weed infestation can create a warning system based on current and previous environmental factors.

Smart farming is a farming system in which AI and cutting-edge technologies are merged with traditional farming practices to improve agricultural products while reducing inputs (Glaroudis et al., 2020). IoT can create interconnections between different objects, such as smartphones, robots, sensors, and weather stations, through the Internet as the primary backbone of the communication channel (Agrawal & Das, 2011; Shahzadi et al., 2016). Using ubiquitous computing and unique identifiers (Agrawal & Das, 2011), IoT can connect humans and machines through a highly distributed network (Shahzadi et al., 2016).

IoT aims to make people's daily lives more sophisticated, flexible, and accessible to anything on the planet (Agrawal & Das, 2011). Novel and effective IoT-based methodologies have been developed to create weed-identification models (Dankhara et al., 2019). These IoT-based intelligent robots use pre-trained models to classify various plant-weed combinations depending on the season, environment, and crops. However, it requires a plant-weed classifier that can distinguish between plants and weeds by analyzing image data using computer vision techniques and labeling them in real time over IoT (Dankhara et al., 2019).

REMOTE SENSING

Remote sensing (RS) resembles the reading process in several ways. It refers to gathering data by utilizing information and communication technology (ICT) services from a distance. More precisely, RS is the science and art of obtaining information about an object, area, or phenomenon by analyzing the data collected by a device not in contact with the object, location, or event under inquiry (Lillesand et al., 2015). Image processing by satellites or UAVs is the most common RS technique (Radoglou-Grammatikis et al., 2020). Electromagnetic radiation is the main component of RS because measurements of reflected radiation from crops allow the collection of essential data on water stress, crop nutritional status, and other field variables (Radoglou-Grammatikis et al., 2020).

As the pressure on farmers to produce crops more effectively and advances in sensor technology, data management, storage, and processing power have increased, RS in agriculture has sparked renewed interest in the last 15 years (Basinger et al., 2020). Agriculture has been one of RS's most extensive application areas of RS since the 1930s (Lillesand et al., 2015). Crop production and biomass have been estimated using RS, water stress, crop nutrient status, herbicide injury, plant diseases, insect damage, and weed detection and control (Basinger et al., 2020).

In weed management, RS usage can reduce the requirements for broadcast herbicide applications, reduce overall input costs, and limit the environmental implications of herbicide use, tillage, soil compaction, and off-target chemical movement (Basinger et al., 2020). It can differentiate between crops and weeds by analyzing image data using computer vision techniques while leaving crops untouched. However, this can be difficult, as many weed and crop species share similar biophysical plant properties (Basinger et al., 2020). Thus, obtaining unique spectral response patterns for each species is also recommended by obtaining multiple image acquisition dates during the growth cycle (Lillesand et al., 2015).

HYPERSPECTRAL IMAGING

Scientists have opted to utilize hyperspectral sensor technology to make the differences between crops and weeds more distinguishable. Unlike regular cameras, hyperspectral remote sensing captures solar radiation reflected off plant surfaces in narrow wavelength bands gathered between 350 and 2,500 nm, allowing for excellent spectral resolution (Basinger et al., 2020). Meanwhile, visible light (color photographs and human eyes) is limited to the RGB spectrum ranging from 300 to 700 nm, which lies in the red, green, and blue (RGB) spectra. With hundreds of spectral bands, hyperspectral simultaneously captures spectral and spatial data (Zhang et al., 2019).

Several models for hyperspectral sensors are regularly used in unmanned aerial vehicle (UAV) applications (Table 2). As each hyperspectral sensor can only detect a limited number of bands, the goal of the survey must be clearly defined to select the most appropriate sensor (Esposito et al., 2021). The spectral signatures of common green weeds and plants in the visible spectrum (RGB) were quite similar, and many of them overlapped, with a slight peak in green reflectance (Roslin et al., 2021). However, wavelengths outside the visible range, such as near-infrared (701–1,300 nm), shortwave-infrared I (1,301–1,900 nm), and shortwave-infrared II (1,901–2,500 nm), can help distinguish between species

Table 2
Hyperspectral sensors and their main characteristics

Camera model	Lens	Spectral range (µm)	Spectral bands (number and µm)	Weight (kg)
CUBERT	Snapshot + PAN	450–995	125 (8 µm)	0.5
Cornirg microHSI 410 SHARK	CCD/CMOS	400–1000	300 (2 µm)	0.7
Rikola Ltd. hyperspectral camera	CMOS	500–900	40 (10 µm)	0.6
Specim-AISA KESTREL16	Push-broom	600–1640	350 (3–8 µm)	2.5
Headwall Photonics Micro-hyperspec X-series NIR	InGaAs	900–1700	62 (12.9 µm)	1.1

Source: Esposito et al. (2021)

as the reflectance may separate from each other (Basinger et al., 2020). The quantity and radiometric range of bands must be carefully considered when dealing with hyperspectral applications (Esposito et al., 2021).

Although hyperspectral sensors have become more affordable recently, they are still significantly upfront compared with RGB and multispectral sensors (Esposito et al., 2021). Furthermore, they are heavier and larger than other sensors, making their assembly on UAV systems challenging and extremely payload intensive. Because hyperspectral imaging provides both spectral and image information, it has enormous potential for plant identification. However, determining which combination of input factors contributes the most to model accuracy requires a greater understanding of the hyperspectral images of crops and weeds (Su, 2020).

HYPERSPECTRAL REFLECTANCE ON DIFFERENT SPECIES, PHENOLOGICAL STAGES, AND CLIMATE

Although hyperspectral remote sensing has been successfully used to discriminate between crop and weed species in field settings, these studies have been limited to only a few crops and plant species (Basinger et al., 2020). Weeds, including sedges, have distinct spectral signatures that can be used as guides for detecting weeds in rice fields using RS (Norasma et al., 2020). Figure 2 shows an example of a different spectral band for the weeds. Spectral information can also be helpful for real-time decision-making, which can be presented on farmers' smartphones or even toward automation and robotic mechanisms to make a suitable response (Alam et al., 2014). Furthermore, the spectrum differences can be explained by combining field data on optical functional features with the canopy radiative transfer model (Punalekar et al., 2016).

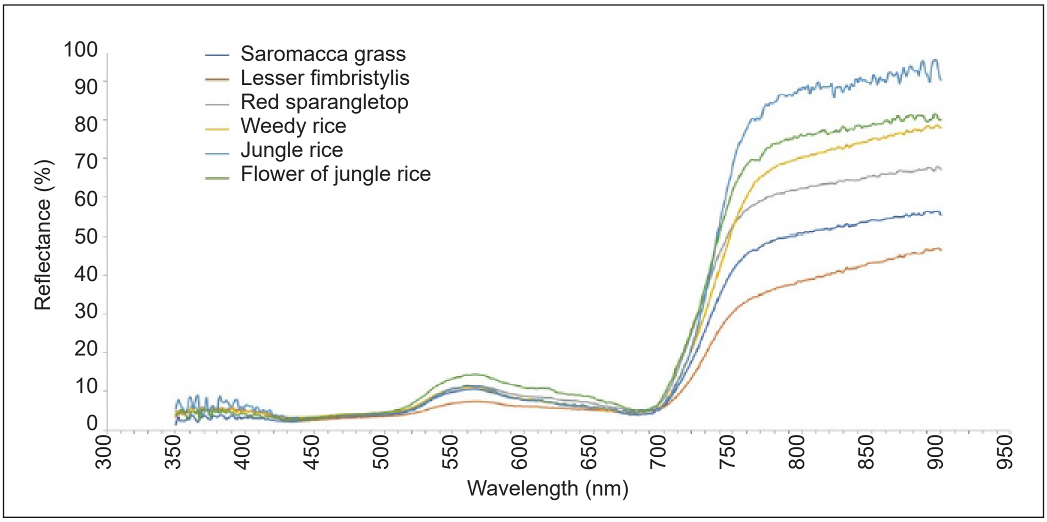


Figure 2. Graph overlays of spectral reflectance of rice weeds (Adapted from Roslin et al., 2021)

Vegetation undergoes several phenological stages during development. Plant physiology changes during these stages, leading to changes in biochemical, biophysical, and structural characteristics (Lausch et al., 2015). As crop traits change throughout the growing season, it is essential to use images taken at different times throughout the growing cycle for crop identification. Multiple image acquisition dates may be required to obtain distinct spectral response patterns for each plant species, including sedge weeds (Lillesand et al., 2015).

Phenological variations can alter species differentiation and can be exploited to improve weed detection accuracy using hyperspectral remote sensing data (Basinger et al., 2020). Combined with visible light and near-infrared reflectance, shortwave-infrared I and II wavelengths can differentiate across plant phenologies and should thus be investigated for future sensor technologies for species differentiation (Basinger et al., 2020). Moreover, the gravimetric water content of barley was found to be the most relevant characteristic for distinguishing between phenological macrostages (Lausch et al., 2015). Plant phenological development involves several biochemical and biophysical vegetation features in vegetation change, which can be captured in great detail using hyperspectral remote sensing technologies (Lausch et al., 2015).

The phenological stages of sedges can be divided into three phases by characterizing the sowing to emergence sub-periods (SOW–EME), emergence to the emission of the floral tassel (EME–EMI), and emission of the floral tassel to physiological maturity (EMI–MAT) (Voss et al., 2021). EME, EMI, and MAT were defined as the emergence of the first 50% of the total seedlings, the emission of the floral tassel (> 2 cm), and the physiological maturation of the seeds (brown color). After the first week of sedge planting, the thick waxy cuticular layer combined with a thick upper epidermis and uniformly distributed Kranz anatomy, which is prevalent in C4 plants, can result in brighter reflectance readings (Basinger et al., 2020).

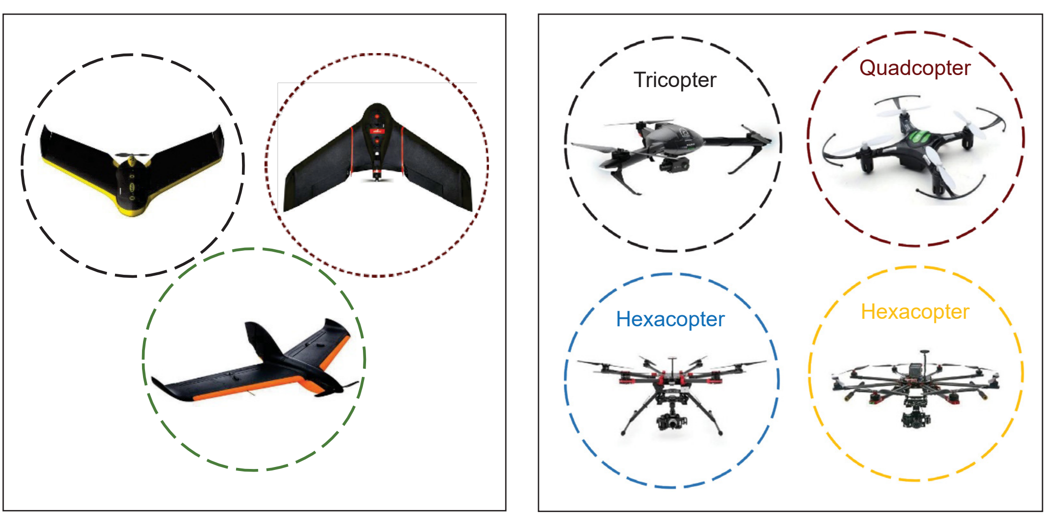
Besides plant species and phenological stages, climate change can contribute to spectral reflectance differences. Even when a similar species enters the same phenological stages, a difference in the spectral band of two individual plants may occur because of different climate influences. Changes in biochemical–biophysical traits caused by weed or plant adaptation to climate change may influence spectral readings at a specific wavelength. Due to genetic variety and physiological plasticity (Varanasi et al., 2016), weeds respond quickly to resource changes. They can flourish in diverse ecosystems more than crops, which may create more distinguishable spectral differences.

Shifts in temperature trends, soil and water acidity, wind and water current patterns, seasonal duration changes, and other factors can all influence differences in spectrum responses (Arias et al., 2021). The use of hyperspectral remote sensing can estimate leaf chlorophyll content (SPAD) and leaf area index (LAI), which are influenced by changes in temperature and CO_2 (Xie et al., 2013). Although CO_2 significantly contributes to climate change, a few Australian researchers have suggested that weed species respond differently when rainfall patterns change (Ramesh et al., 2017). Because of the changeable environment, which deals with various dynamic and complex aspects, requires an adequate record of spectral observations over multiple decades, if possible (Arias et al., 2021), to forecast the sedge invasion of rice fields.

AIRBORNE HYPERSPECTRAL

A hyperspectral camera can be embedded in a UAV, a flying robot with several configurations (Figure 3), and a standard tool in precision agriculture (Radoglou-Grammatikis et al., 2020). UAVs are frequently the first choice for fast and precise in-situ remote sensing or survey operations because of their affordability, user-friendliness, and versatility (Esposito et al., 2021). The UAV does not require a human pilot onboard and can be considered a flying IoT (Bhoi et al., 2021). In recent years, there has been a noticeable trend toward developing lightweight, portable hyperspectral equipment that can be deployed on UAVs and other tiny platforms (Lillesand et al., 2015).

UAVs can be grouped based on several technical characteristics, including aerodynamic features, autonomy level, size, weight, and power sources (Radoglou-Grammatikis et al., 2020). UAVs can be categorized into monitoring, spraying, and multiple applications. Data collected by UAV sensors can be spectral, spatial, or temporal. The ability to undertake monitoring and spraying missions can improve agriculture usage by maximizing the efficacy of pesticides and fertilizers, detecting potential pests and illnesses on time, and simplifying spraying procedures (Radoglou-Grammatikis et al., 2020).



(a) (b)

Figure 3. Several types of (a) fixed-wing and (b) rotary-wing UAVs (Adapted from Radoglou-Grammatikis et al., 2020)

CONCLUSION

This review summarizes the advance made in our understanding of the hyperspectral reflectance of the weedy sedge in rice fields. This review also discusses how they interact with climate change and phenological stages to forecast the sedge invasion. Sedge weed infestation in rice fields can cause severe yield loss if improperly handled. Climate change alters weed distribution in rice fields, affecting weed management as it depends on weed species' appearance and distribution. The spectral signature of sedges can be used for weed monitoring, and this method can save a lot of time and labor by utilizing RS technology and drones. The infrared region may display significant differences in the spectral reflectance of sedge weeds using hyperspectral sensors. AI technology with deep learning can analyze physiological and morphological changes for sedge outbreak detection. Forecasting and IoT real-time monitoring methods can be integrated with the decision support system, which stakeholders can use to take appropriate action. UAVs and hyperspectral sensors accurately identify weed species in cultivated rice fields and can improve weed management sustainability. The excellent capabilities of UAV technology can provide comprehensive analysis in the context of precision agriculture. Because of the importance of the phenological stage and climate change on sedge species classification using hyperspectral sensors, future studies should consider phenology and abiotic factors when investigating the spectral signature of sedge species in wetland rice fields.

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