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Review Article

Integration of Unmanned Aerial Vehicle and Multispectral Sensor for Paddy Growth Monitoring Application: A Review

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ABSTRACT

Using a conventional approach via visual observation on the ground, farmers encounter difficulties monitoring the entire paddy field area, and it is time-consuming to do manually. The application of unmanned aerial vehicles (UAVs) could help farmers optimise inputs such as water and fertiliser to increase yield, productivity, and quality, allowing them to manage their operations at lower costs and with minimum environmental impact. Therefore, this article aims to provide an overview of the integration of UAV and multispectral sensors in monitoring paddy growth applications based on vegetation indices and soil plant analysis development (SPAD) data. The article briefly describes current rice production in Malaysia and a general concept of precision agriculture technologies. The application of multispectral sensors integrated with UAVs in monitoring paddy growth is highlighted. Previous research on aerial imagery derived from the multispectral sensor using the normalised difference vegetation index (NDVI) is explored to provide information regarding the health condition of the paddy. Validation of the paddy growth map using SPAD data in determining the leaf's relative chlorophyll and nitrogen content is also being discussed. Implementation of precision agriculture among low-income farmers could provide

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valuable insights into the practical implications of this review. With ongoing education, training and experience, farmers can eventually manage the UAV independently in the field. This article concludes with a future research direction regarding the production of growth maps for other crops using a variety of vegetation indices and map validation using the SPAD metre values.

Keywords: Multispectral, normalised difference vegetation index, paddy field, soil plant analysis development, unmanned aerial vehicle

INTRODUCTION

Rice (*Oryza sativa* L.*)* is the main food source for about half of the world's population, with 90% produced by Asian countries. However, the country-of-origin exports only 7% of the global rice production (Othman et al., 2020). Therefore, rice plays a major role in sociocultural development, food security, and government strategic intervention in developing countries, including Malaysia (Seglah et al., 2020). The country's rice policy aims to accomplish three goals: to enhance balanced income to maintain price stability, increase income for farmers, and gain consumer supply security (Akhtar & Masud, 2022). Almost 40% of Malaysian farmers rely solely on paddy cultivation.

Malaysia's rice production stood at 2.9 and 1.88 million MT, respectively, in early 2019, with the country's self-sufficiency level reported at 72.85%. Fast forward, the national SSL has dropped slightly to 69% as a result of the looming COVID-19 pandemic, which has caused food supply chain disruption and increased consumption of staple foods (Omar et al., 2020). Although rice annual production grows at a 1.6% rate, this rate is insufficient to meet the population's consumption needs. The national average rice yield is around 4.2 tonnes per acre. High-yield granaries are in IADA Barat Laut Selangor, IADA Pulau Pinang, IADA Ketara, and MADA. In contrast, the low-yield granaries are in Kemasin, IADA Pekan, and Rompin (Ministry of Agriculture, 2016). Problems farmers face in rice cultivation include climate change, invasive and native pests, reduced fertility of the soil health due to excessive fertiliser, poor nutrition management, water shortages, and pesticide-related health problems.

In general, paddy monitoring depends on ground-based surveys and visual observation to determine plant health conditions in a small farm area by evaluating a plant based on the conditions of its leaf (Gée et al., 2021). However, paddy assessment requires information that is higher than the canopy level. Data collection and validation techniques such as manual inspection and perimeter scouting are inefficient because they are time-consuming and costly (Gracia-Romero et al., 2017). Precision agriculture through site-specific crop management provides an alternative to this issue (Ponnusamy & Natarajan, 2021). It can potentially increase rice production to 10 mt/ha, thus addressing issues such as land scarcity, rising production costs, and inefficient paddy monitoring by farmers (Bujang & Bakar, 2019). Profitability for farmers may improve as agricultural operations are managed more efficiently and able to predict yield before harvest, resulting in less strain on human resources and higher productivity levels. However, weather problems and conventional remote sensing techniques via sensor installation in the field limit data collection efficiency (Nguy-Robertson et al., 2012). Using a satellite and a piloted plane poses constraints due to low spatial and temporal resolution to capture the paddy images, resulting in low pixel resolution and unclear images. Conversely, UAVs that fly at a lower altitude generate higher spatial resolution images of the crops, with each pixel being a centimetre or millimetre (Pérez-Ortiz et al., 2016).

Unmanned aerial vehicles (UAVs) have now developed from slow-flying UAVs to fixed-wing and rotary-wing UAVs, which have gliding characteristics and require less manpower. UAVs with visible bands and multispectral scanning sensors can collect data to analyse crop growth, plant health conditions, maturity, and morphology (Olson & Anderson, 2021). The use of UAV with a multispectral sensor produces a high spatial resolution image, i.e., 3.47 cm in monitoring wheat scab during the wheat filling stage, in which support vector machine (SVM) regression has 81% accuracy for the training set and 83% for the verification set (Zhu et al., 2022). In terms of paddy, applications of aerial images generated from multispectral sensor mounted on a UAV include drought damage assessment for crop fields in Indonesia, determination of crop health in Brunei and identification of the relationship between the rice lodging and available nitrogen in soil content by assessing their spatial distributions images in a crop field in Japan (Iwahashi et al., 2022; Elfri et al., 2023; Sato et al., 2023).

Numerous vegetation indices derived by UAVs were demonstrated in detecting plant diseases, crop performance, and use of consumption on the farm (Roth et al., 2022; Boursianis et al., 2022; Feng et al., 2022). It also employs the near-infrared (NIR) and visible electromagnetic spectrum regions to determine the crop quality. Vegetation indices such as the integrated, simple ratio (R_{515}/R_{570}), i.e., band rationing and transformed chlorophyll absorption reflectance index/optimised soil-adjusted vegetation index (TCARI/OSAVI), narrow-band indices to estimate leaf chlorophyll and crop growth are measured based on a multispectral sensor integrated with UAV (Wang et al., 2019). Corti et al. (2019) demonstrated that colour-infrared film combined with a low-cost automated camera can generate an NDVI map suitable for crop monitoring.

Instruments based on optical qualities are split into the leaf scale and the canopy scale, depending on the extent of use. UAV captures images of paddy growth, which are analysed using vegetation indices and SPAD metre values. The previous study used SPAD values to construct a relationship with spectral and textural indices. In contrast, the stepwise regression model (SRM) was used to determine the best combination of spectral and textural indices in estimating SPAD metre values. For example, support vector machine (SVM) and random forest (RF) models are used to estimate SPAD values based on optimal combinations (Guo et al., 2022).

The different approach shows that SPAD metre values were gathered as surrogates of plant nitrogen content to create relationships on various days after transplanting for converting nitrogen index maps to SPAD maps of paddy for potential variable rate fertiliser application control (Wang et al., 2022). Vegetation indices displayed on the map allow for determining the amount of chlorophyll concentration present in rice on the images taken through the UAV that correlate with SPAD metre readings. Therefore, this review aims to elaborate on the application of UAV-mounted multispectral sensors in monitoring paddy based on vegetation indices and SPAD metre values.

OVERVIEW OF RICE PRODUCTION IN MALAYSIA

The top three rice-producing countries; Indonesia, Vietnam, and Thailand, have allocated 11.50 million hectares, 7.54 million hectares, and 10.83 million hectares for paddy plantation areas (USDA, 2020). Among the Southeast Asian rice-producing countries, the average productivity of granaries in Malaysia comes in third, after Vietnam and Indonesia (Table 1). Malaysia has the smallest total paddy rice planting areas in Southeast Asia, with 689,268 ha (Firdaus et al., 2020), with Peninsular Malaysia accounting for two-thirds of the total planting area, whereas Sabah and Sarawak account for the remaining one-third (Ramli et al., 2012).

Paddy is one of the most crucial crops in Malaysia. Around 195000 farmers work hard to improve rice cultivation and productivity (Omar et al., 2019). The varieties local farmers produce include white rice, glutinous rice, black rice, red rice, brown rice, and aromatic rice. It provides income and livelihood for the community near paddy planting areas, mostly small farmers and landless agricultural workers. Most farmers live in larger paddy fields near granary sites with smaller paddy fields across the country (Fahmi et al., 2013).

Granaries are rice farms with adequate irrigation systems and land areas of more than 4,000 ha (Rahmat et al., 2019). Malaysia has eight main granary areas representing the country's rice bowl and serving as the food security supply. Paddy is mostly planted in the northern and eastern parts of Peninsular Malaysia, especially in Kedah and Kelantan. Such areas in Kedah

Table 1
Paddy productivity in the selected Southeast Asian countries in 2017

Country	Productivity (mt/ha)
Malaysia	4.47
Vietnam	5.89
Indonesia	4.76
Myanmar	2.91
Philippines	4.02
Laos	3.24
Cambodia	2.78
Thailand	2.89
Brunei	2.00

and Kelantan are suitable for rice farming due to the flat lowland and the soil type. Besides these recognised granaries, Malaysia has 74 secondary granaries and 172 minor granaries that contribute up to 28,441 and 47,653 hectares, respectively (Rahmat et al., 2019). The average yield per hectare was 2,311 kg/ha, whereas rice production was 2,748 mt in 2020 (Table 2).

Under the National Agricultural Policy (1984–1991), the development of main granary areas was initially reserved as the gazetted wetland paddy areas (Ministry of Agiculture, 1984). It is deemed a strategic intervention to support the paddy growth and rice industry, as well as to protect the national food security. Granary areas in Malaysia are managed by agencies such as (1) Muda Agricultural Development Authority (MADA), (2) Kemubu Agricultural Development Authority (KADA), (3) North Terengganu Integrated Agriculture Development (KETARA), (4) Project Barat Laut Selangor (PBLS), (5) Krian, (6) Seberang Perak, (7) Seberang Perai, (8) Kemasin, (9) Rompin, (10) Kota Belud, and (11) Batang Lupar. To date, granaries under KETARA, IADA Pulau Pinang, MADA, and Barat Laut Selangor have exceeded the average granary productivity per hectare. However, the average yield per hectare varies between granary areas due to geographical factors that are influenced by environmental conditions, cultivated areas, and field-based agricultural strategies (Omar et al., 2019).

Malaysians require around 110 kg of paddy per capita per year to meet the individual rice consumption (Dorairaj & Govender, 2023). Malaysians consume approximately 82.3 kg of rice annually, and the paddy field produces 3.7 metric tonnes of rice each hectare (Rusli et al., 2024). Adults consume about 2.5 plates of white rice per day (Kasim et al., 2018). This trend is expected to increase yearly since the country's population is growing. The government has set a target of increasing local rice production by up to 75% in 2022−2023 (The Star, 2019). From 2016 to 2020, the government focused on food security via sustainable measures to address the food availability and accessibility issues, especially in terms of the nation's rice consumption and production (Adnan et al., 2021).

The self-sufficiency level of the national rice production and consumption fluctuates between 67% and 70%. Rice security reflects the nation's food security; hence, accomplishing self-sufficiency through sustainable paddy farming is crucial. The Ministry of Agriculture and Food Industries (MAFI) is in charge of sustainable paddy farming via its agency, namely the Integrated Agricultural Development Authority (IADA). This agency monitors rice production to fulfil 72% of the country's demand, yet Malaysian rice productivity is still low. Malaysia imported about 740,000 tonnes of rice in 2018 for RM1.18 billion (The Star, 2019). Consequently, the government stepped up with an action plan by establishing the National Agricultural Policy (Dardak, 2015; Osman & Shahiri, 2017).

However, rice production in Malaysia has faced several challenges, including extreme weather, poor soil fertility and nutrient management, avoidance of genetically modified

Table 2
Total paddy production and productivity of the main granary areas in Malaysia from 2016 to 2020

Year	2016		2017		2018		2019		2020	
Granary	Average Yield (kg/ha)	Paddy Production (mt)	Average Yield (kg/ha)	Paddy Production (mt)	Average Yield (kg/ha)	Paddy Production (mt)	Average Yield (kg/ha)	Paddy Production (mt)	Average Yield (kg/ha)	Paddy Production (mt)
MADA	5284	1063247	4841	974387	5111	1028867	4933	993206	5611	1129218
KADA	4610	248172	4448	240490	4695	252149	4032	203011	5082	272975
KERIAN	3949	165027	4087	171237	3957	165790	3584	150162	4403	185039
IADA BLS	5825	222033	4510	165571	4731	174432	4756	174088	5600	206456
IADA PULAU PINANG	5801	148297	5737	146660	5228	133636	4660	119116	6178	157929
IADA SEBERANG PERAK	3729	103388	3180	88198	3417	94784	2923	79884	3788	105466
IADA KETARA	5623	54836	5172	50438	5349	52164	5162	50335	5828	58022
KEMASIN SEMERAK	3771	27456	3779	26938	4079	28154	3733	28233	4294	30418
PEKAN	2052	13425	1506	10286	2673	17183	2642	17562	2323	14943
ROMPIN	2793	14436	3338	17028	2910	14756	23773	12120	3454	17227
KOTA BELUD			2511	22805	3112	30096	2908	25598	3086	29037
BATANG LUPAR			2009	2252	2492	2794	2754	3087	2311	2748

Source. https://www.doa.gov.my/index.php/pages/view/1053 planting materials, and application of remote sensing constraints by farmers to monitor paddy growth conditions. Food security or the livelihood of farmers is vulnerable to functional fluctuations in global supply chains to maintain international rice trading ties. During the unprecedented COVID-19 pandemic, the movement control order (MCO) period has caused significant disruption in the food supply chain. Malaysia encountered a volatile rice import trend during the early stage of the pandemic, making it difficult to secure a committed rice trading partner. Therefore, improved paddy monitoring methods for precision agriculture in Malaysia can offer better crop health and resilience in the rice production system.

PRECISION AGRICULTURE

According to the International Society for Precision Agriculture, precision agriculture is "a management strategy which collects, processes, and analyses temporal, spatial, and single data and merges it with other information to support management decisions to improve resource use efficiency, productivity, profitability, quality, and sustainability of crop yields based on estimated variability" (Onyango et al., 2021). Precision agriculture is associated with an increase in the number of actions made per unit area of land for each unit of time to increase the amount and/or quality of productivity and/or the environment and enhance more proactive input consumption (Monteiro et al., 2021). For example, the amount of fertiliser, herbicides, and pesticides will be calculated based on the spatial variability across the field, which is used to calculate the amount needed for a particular crop (Norasma et al., 2019).

Precision agriculture has shifted the emphasis from spatial resolution to superior decision-making, space or time. It is widely used in (1) plant protection and disease control, (2) monitoring crop canopy status, (3) crop water management, (4) map cropping systems, (5) mapping soil fertility and soil types, and (6) predict or map crop yield (Table 3). A variety of technologies, such as soil and crop sensors and global navigation satellite systems (GNSS), which are global positioning systems (GPS), geographic information

Table 3
Different types of applications for precision agriculture technologies

Purpose	Precision agriculture technology	Application	References
Plant protection and disease control	Geostatistical techniques, chlorophyll fluorescence, violet diode laser-induced integrated decision support system for intercropping, a wireless sensor network, continuous time Markov process, UAV, spectral crop sensors, and site-specific application for pesticides	Crop pest and disease detection and monitoring, as well as disease-resistance breeding	Dhau et al. (2018), Nestel et al. (2019), Sui et al. (2016), Low et al. (2020), and Pretorius et al. (2017)

Table 3 *(continue)*

Purpose	Precision agriculture technology	Application	References
Crop growth monitoring	NDVI	Differentiate crops that grow in different environments.	Bazezew et al. (2021)
	Remote sensing	Canopy replication and plant age	Mapfumo et al. (2017)
	Multi-temporal Landsat 8 NDVI anomalies	Detecting and mapping inconsistencies in crop	Chemura et al. (2017)
		Changes in vegetation cover	Meroni et al. (2021)
Crop water management	Thermal time, wireless sensor technology indices of water stress, and simulation models	Water stress detection technology	Gohain et al. (2021), Alou et al. (2018), and Jamroen et al. (2020)
	Use of UAV	Planning and development of irrigation infrastructure	Gauram et al. (2021)
	Precision irrigation	Sufficiency of sprinkler irrigation efficiency	
	Geographical information system (GIS)	Assess the temporal and spatial distribution of irrigation water using the drip irrigation system	Chen et al. (2019)
Mapping cropping system	Recognition of machine vision schemes in satellite pictures	Differentiate the crop field from nearby green vegetation zones	Tsai et al. (2017)
	Simulation models	Estimate the proportion of tree cover inside crops	Della Chiesa et al. (2022)
	Wall-to-wall sub-metre, moderate resolution Landsat 8 imagery and WorldView	Mapping cropland for small-scale farmers	McCarty et al. (2017)
	Wireless sensor nodes	Evaluate the wireless signal for precision agriculture in terms of connection reliability and signal strength.	Karunanithy and Velusamy (2021)
	RapidEye	Mapping maise cropping systems	Richard et al. (2017)
	RapidEye combined with spatial logistic regression modelling	Differentiate land management strategies in rangelands	Ali et al. (2016)
Soil Fertility Mapping	Transect, density regression, and indigenous knowledge are integrated with gamma ray spectrometry and satellite images using non-parametric kernel geostatistical techniques	Spatial variations in soil fertility	Munnaf et al. (2020)
	RapidEye remote sensing	Building estimation models to map out the soil organic carbon	Costa et al. (2018)

Table 3 *(continue)*

Purpose	Precision agriculture technology	Application	References
	Kriged maps	Determining the soil functional qualities	Takoutsing et al. (2017)
	Soil diagnostic and GIS	Establishing fertilizer recommendations based on specific site conditions	Grzebisz et al. (2021)
	Near-infrared reflectance (NIR)	For soil sampling, as well as chemical and physical analyses	Winowiecki et al. (2017)
Yield Prediction/ Mapping	Remote sensing	Discovering agricultural productivity and soil	Irmulatov et al. (2021)
	UAV	Fertility constraints at several spatial scales	
	Vegetation and thermal indices	Estimation of cereal production	
	Random forest classifier	Yield variations in smallholder farming systems	Ibrahim et al. (2021)

systems (GIS), and variable rate applications (VRA), can be used in making decisions. It includes three data collection methods: remote sensing, field sampling, and proximal sensing. Each type of data collection is determined by the parameters monitored in the field.

UNMANNED AERIAL VEHICLE FOR PADDY GROWTH MONITORING

Remote sensing is a data collection tool that observes the characteristics of an object without direct contact over large areas in real time (Janga et al., 2023). For precision agriculture, remote sensing platforms capture the aerial view of the entire farm, consisting of ground-based remote sensing, aerial-based remote sensing, and satellite-based remote sensing (Table 4). These platforms have been applied in paddy mapping because they provide large temporal and spatial information to monitor crop growth. Aerial plane outfitted with cameras is used to capture images of paddy to estimate the irrigated yield, a flexible and effective yield prediction tool. However, the cost of fuel and a professional pilot is expensive.

Aerial-based remote sensing platforms include high-altitude aerial vehicles and low-altitude UAVs. UAVs have been used widely in agriculture applications and have emerged as a remote sensing tool for yield prediction due to their high resolution, high throughput, and low cost (Zhang & Zhu, 2023). UAVs collect data to measure parameters such as leaf area index (LAI) and height, allowing growth control for paddy. UAVs can be used to measure common vegetation index to determine diseased plant tissues and map the defect size. On the other hand, water management is an important aspect of UAV application, as precision irrigation techniques in paddy fields improve crop management efficiency by reducing wastage in the usage of fertiliser, water, and pesticides (Mallareddy et al., 2023).

Table 4
Comparison of quality of services between different types of remote sensing platforms in precision agriculture

Quality of services	Types of remote sensing platforms			
	UAV	Satellite	Manned Aircraft	Ground Based
Flexibility	High	Low	Low	Low
Adaptability	High	Low	Low	Low
Cost	Low	High	High	Low
Time Consumption	Low	Low	Low	High
Risk	Low	Average	High	Low
Accuracy	High	Low	High	Moderate
Deployment	Easy	Difficult	Complex	Moderate
Feasibility	Yes	No	No	Yes
Availability	Yes	No	Yes	No
Operability	Easy	Complex	Complex	Easy

UAVs are equipped with high-resolution sensors that acquire more detailed vegetation phenotypic information to predict yield than manned aircraft and satellites. This technology is now used to gather high-quality images by mounting specified bands, including NIR (near-infrared) and IR (infrared), and as sensors, including RGB (red-green-blue), multispectral, hyperspectral, and thermal. Sensors are selected to monitor various parameters such as resolution, weight, captured images, optical quality, and price. One RGB would be sufficient for mapping paddy planting areas and extracting pure crop canopy information (Kazemi & Parmehr, 2023). Images generated from RGB can extract information such as vegetation structure and reflectance for growth monitoring and biomass estimation. RGB requires low cost and is useful for UAV applications such as orthomosaic creation because it can capture high-resolution images. In addition, they function well in different weather conditions, be it sunny or cloudy. However, due to the limited spectral range, they cannot analyse many vegetation indices.

Unlike digital RGB cameras that only capture images in the visible range, multispectral sensor can capture images in multiple spectral bands, including NIR, which provides additional spectral information to estimate yield by calculating vegetation indexes. Multispectral and hyperspectral can collect data using various spectral channels to obtain high-quality images to assess a variety of physical and biological characteristics of paddy. Unlike satellites, which have a fixed number and type of sensors, UAVs can be modified to be equipped with specific sensors to meet specific needs. Multispectral and hyperspectral are suitable for disease detection because they have many bands that are sensitive in detecting disease symptoms. In contrast, thermal is used to collect temperature data, and its usage in irrigation activities is more effective (Tsouros et al., 2019).

Because RGB and multispectral sensor are less expensive, researchers often use small or medium-sized UAVs for field trials. Most multispectral can only acquire a small amount of spectral information in the visible and NIR bands at low spectral resolution. Hyperspectral sensor, on the other hand, provide higher spectral resolution and more continuous spectral information than multispectral. Besides, multispectral and hyperspectral have specific weather requirements to perform their tasks, which must acquire images in clear and cloud-free conditions.

Multirotor UAVs, fixed-wing UAVs, and unmanned helicopters are the types of UAVs used in agriculture. Most UAVs for field phenotyping fly at an altitude of less than 150 m, and the image resolution can reach centimetres (Stöcker et al., 2017). Multirotor UAVs can hover and turn in the air (Fu et al., 2020), but they consume much power, resulting in short battery life, usually less than 30 minutes. Furthermore, due to their small payload, multirotor UAVs can only carry a limited number and type of sensors. Fixed-wing UAVs can fly at high speed for longer periods, allowing them to cover a large area of farmland in a short amount of time. Moreover, fixed-wing UAVs with large wings have larger payloads, which can provide a wider sensor array. Fixed-wing UAVs, however, cannot collect data in small-scale farms due to the long runways required for take-off and landing, besides being unable to hover and turn flexibly in the air.

PADDY GROWTH MONITORING BASED ON AERIAL IMAGERY GENERATED FROM MULTISPECTRAL SENSOR

Some locations in the paddy field may not be easily recognised or easily accessible for ground visual observation on the ground (Rosle et al., 2022). In addition, some of the farmers are elderly, so they are sometimes unable to check the entire area due to a lack of energy. Thus, it could cause inefficient paddy field management. The farm manager can now view the entire paddy field using aerial imagery without missing any locations. Therefore, aerial imagery using multispectral sensors can assist farm management in constantly monitoring paddy with ground surveying for validation (Lu et al., 2021; Sari et al., 2021).

Multispectral is often lightweight, compact, and particularly straightforward to operate on the UAV. In addition, the cost of multispectral is reasonable and will get cheaper in the future. An interference filter installed at the front of the camera lens to filter or transmit specific lights is used to create a multi-band filter and multispectral sensor. Compared to RGB, a multispectral provides more wavebands in visible and NIR spectral ranges (Figure 1) and can predict yield, biomass, nitrogen content, and other parameters. Multispectral sensor employ a variety of common spectral bands such as red, green, blue, red-edge, and NIR. They are classified into bandwidth categories: narrow-band and broadband (Deng et al., 2018). The multispectral sensor consists of at least four bands. The difference in the number of wavebands depends on the manufacturing (Figure 2) (Xie & Yang, 2020).

It is important to understand how monochrome and colour work. A photo-sensing element in monochrome cameras comprises a two-dimensional array of sensitive pixels.

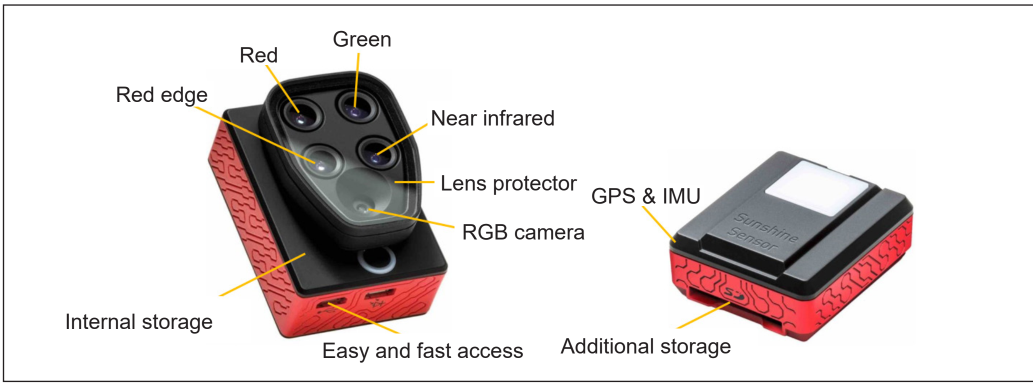

Figure 1. Multispectral sensor

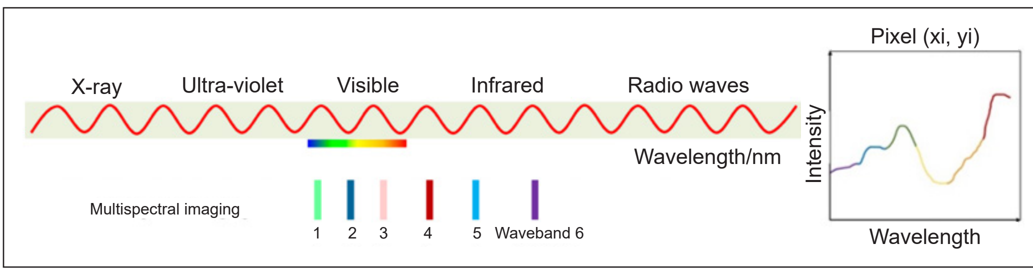

Figure 2. Multispectral imaging with six wavebands (Adapted from Abijo et al., 2023)

In monochrome CMOS image sensing, these pixels are sensitive to light emitted across a broad spectral range. A colour camera has an image that detects elements with a two-dimensional array of pixels. The remote-sensing multispectral sensor is coated with a mosaic colour pattern that transmits red, green, or blue lights. The colour pigments create the colour filter array (CFA), known as the RGB cameras (Hassan et al., 2021). Examples of multispectral sensors are Green Seeker (ground sensor) and Landsat 8 (Satellite sensor). Multispectral sensor such as RedEdge (MicaSense, Inc., Seattle, WA, USA) (Figure 3), MCA 6 (Tetramcam Inc., USA), and DJI Mavic 3 Multispectral (DJI, China) can capture images from the visible and NIR bands.

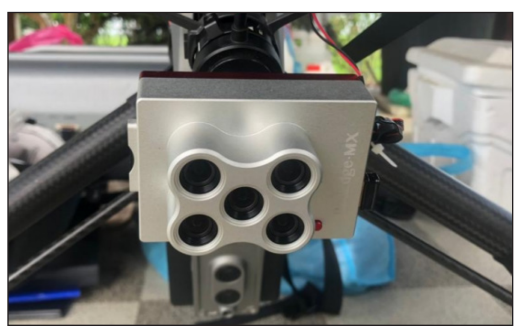

Figure 3. MicaSense-RedEdge-MX multispectral sensor

Multispectral imagery consists of 3−10 distinguished "wider" bands. The images produced can be further analysed with GIS or RS software. Norasma et al. (2019) used a MicaSense sensor to create the rice growth map. This sensor is also used by Jiang et al.

(2020) to monitor the operation parameters of low-altitude UAVs in acquiring the NDVI values across paddy fields. Therefore, the sensor can help farmers overcome the issues in the field within a shorter period. Figure 4a shows the RedEdge-MX multispectral sensor's spectral resolution, and Figure 4b illustrates the spectral reflectance graph of healthy and stressed plants through five bands. The MicaSense RedEdge-MX can capture five types of wavebands, including red, green, blue, red edge, and NIR. Red band and NIR are utilised in the NDVI algorithm.

The principle underlying high accuracy is the use of various electromagnetic spectrum bands. They not only contribute to the data from the images obtained, but they also generate vegetation indices. Luo et al. (2022) applied multispectral sensor to map paddy fields at different growth durations (booting and heading stages) using normalised difference vegetation index (NDVI), red-edge chlorophyll index (CIred edge), green-edge chlorophyll index (CIgreen edge), two-band enhanced vegetation index (EVI2), normalised difference red edge (NDRE), wide dynamic range vegetation index (WDRVI), MERIS

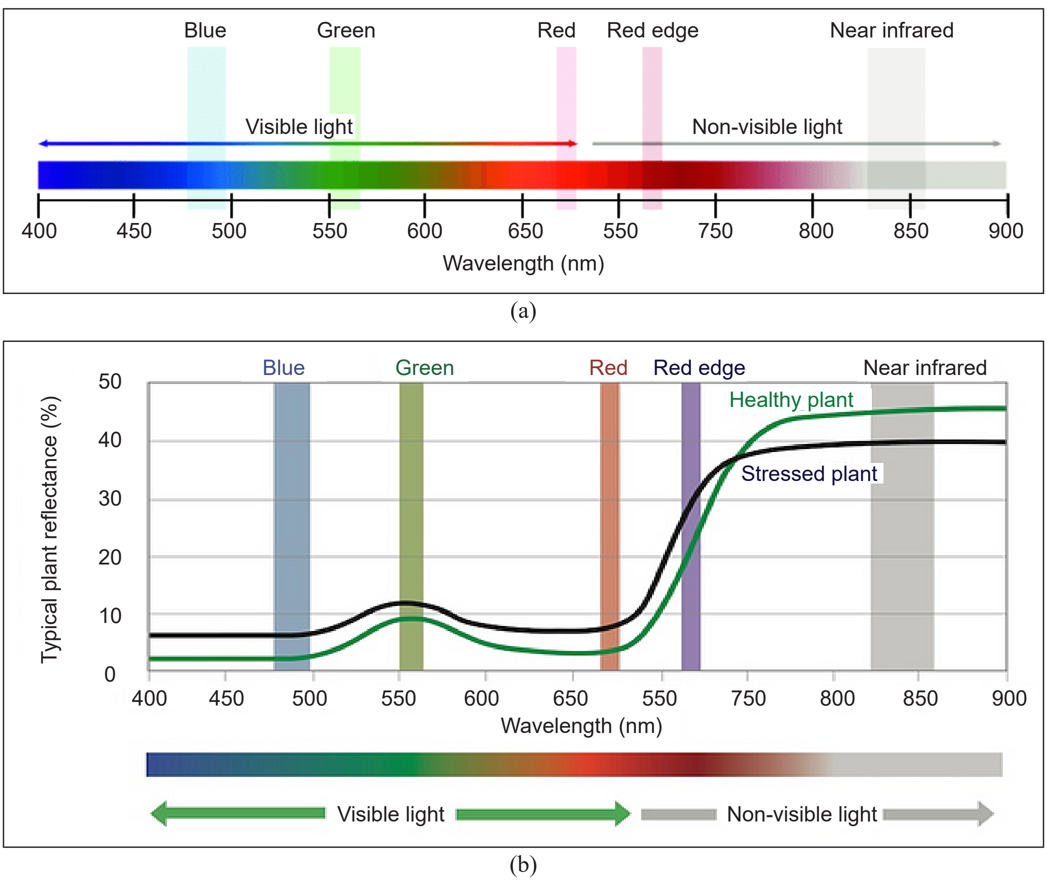

Figure 4. (a) The spectral resolution of the MicaSense-RedEdge-MX multispectral sensor; (b) Reflectance curve of the healthy and stressed plant (Roman & Ursu, 2016)

terrestrial chlorophyll index (MTCI), Normalised Difference Red Edge (Ndre) and soil-adjusted vegetation index (SAVI). Most aerial images for crop health monitoring employ multispectral sensor (Hassler et al., 2019) that generate vegetation indices such as NDVI, NDRE, and GNDRE (Kalischuk et al., 2019; Barbedo, 2019).

Vegetation indices are the most essential criteria in crop disease identification. However, the multispectral sensor requires high cost and additional work to calibrate the specific functions of the indices, including disease identification and image processing. Furthermore, multispectral sensors make it difficult to detect small changes in terms of the biophysical and biochemical characteristics of crops (Neupane & Baysal-Gurel, 2021). However, the price will be reduced in the future, and the image processing will be easier to work on.

VEGETATION INDICES FOR PADDY GROWTH MONITORING

Data captured from UAVs is expressed using indices, including the vegetation index. Souza et al. (2020) used active and passive sensors to obtain vegetation index maps to assess crop growth. The electromagnetic spectrum is a range of all types of electromagnetic radiation based on frequency and wavelength. Each electromagnetic wave is classified according to the specific frequency, photon energies, and wavelengths. In a remote sensing context, the electromagnetic spectrum provides valuable information on the crops' condition. For example, necrosis of the leaves can be visualised under the visible light wavelength. The changes on the leaves can be detected in the visible spectrum, as well as in other electromagnetic spectra, such as the vegetation index light band (Hogan et al., 2017).

Consecutive crop monitoring enables farmers to identify small changes that are difficult to detect with the naked eye. Multispectral imaging, for instance, is useful to analyse paddy health using NDVI indices. In addition, it allows an evaluation of the absorption degree of solar radiation in certain bands; thus, the crop's health can be monitored (Ishihara et al., 2015). NDVI can be derived from satellite imagery such as Pour l'Observation de la Terre (SPOT), moderate resolution imaging spectroradiometer (MODIS), and Landsat. Nevertheless, the low temporal and spatial resolutions enhance reliable crop monitoring at the field level, particularly to obtain information for smallholder farmers. UAVs can provide high spatial resolution at 0.05 to 1-metre resolution, and the data is useful to identify the condition of certain plants. Based on aerial images, farmers can monitor the field using NDVI values.

The NDVI value can be the indicator to determine the crop conditions. However, soil colour, cloud shadow, soil brightness, leaf canopy shadow, and atmosphere have an impact on NDVI value, which needs remote sensing calibration. The NDVI equation is shown as Equation 1:

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{RED}) / (\mathrm{NIR} + \mathrm{RED}) \qquad (1)$$

where NIR represents the reflectance value of the NIR band; RED represents the reflectance value of the red band.

The plant greenness density is referred to detect phenological changes during the planting period. NDVI is one of the most practical vegetation indices to quantify greenness on the vegetation land cover (Roy et al., 2016). NDVI is constructed according to the red and NIR bands to identify crop health conditions, as well as monitor crop growth. The NDVI values normalise the reflectance captured from images from -1 to 1. Positive values indicate higher vegetation (vigour), while negative values indicate unvegetated surfaces such as cities, water, barren soil/land, and ice (Sishodia et al., 2020). The NDVI values of 0−0.33 indicate unhealthy or stressed conditions, 0.33−0.66 indicate moderately healthy conditions, whereas 0.66−1 signifies very healthy conditions, as illustrated in Figure 5 (Rosle et al., 2019). However, the range can be different for other crops, which requires further analysis.

NDVI is commonly evaluated in rice-related research as an important indicator of rice growth (Fenghua et al., 2016). The enhanced vegetation index (EVI), like NDVI, has received much attention in monitoring vegetation quality, where it also has multispectral capabilities. It is shown as an optimised vegetation index developed by Liu and Huete to improve the vegetation signal's sensitivity in high biomass areas. The primary application of EVI is to rectify NDVI results for atmospheric changes and serve as soil background signals, primarily in dense canopy zones. The EVI equation is shown as Equation 2:

$$EVI = 2.5\ (NIR - RED) / (NIR + 6R\text{-}7.5B + 1) \quad (2)$$

In contrast, the Landsat soil-adjusted vegetation index (SAVI) is used to rectify NDVI for the influence of soil brightness in areas with low vegetation cover. It is useful for soil and vegetation monitoring, and it has high-resolution and high-density data equipped with remotely sensed data to provide excellent spatial coverage. However, the calculation is complex since the data obtained are for operational use. The EVI equation is shown as Equation 3:

$$((NIR - R) / (NIR + R + L)) * (1 + L) \quad (3)$$

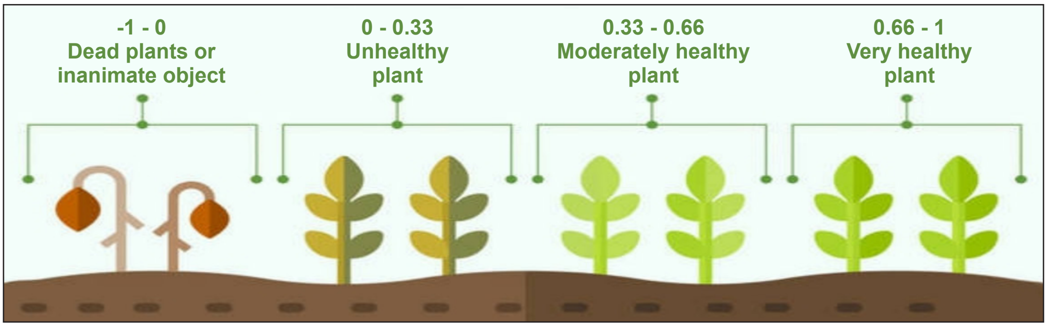

Figure 5. NDVI values of plant health classification (Cherlinka, 2023)

SOIL PLANT ANALYSIS DEVELOPMENT ANALYSIS FOR PADDY GROWTH MONITORING

Chlorophyll is an important pigment for plant photosynthesis because it demonstrates a plant's ability to exchange material energy with its surroundings, as well as carbon sequestration ability, primary productivity, and nitrogen utilisation efficiency. Besides being an important indicator of crop condition, chlorophyll indicates the stage of plant development and growth. It also reflects plant stress. For example, when a disease spreads among plants, the leaves change from green to yellow and, subsequently, brown and white. The spectral characteristics of chlorophyll are essential in determining its content. The green and red bands were found to be the most effective in chlorophyll detection (Chusnah et al., 2023), but some studies have identified the NIR band as a fitting choice (Sharabiani et al., 2023; Raddi et al., 2022).

Previous research has also demonstrated that reflectance spectra in the visible region (400- 979 nm) are capable of estimating chlorophyll (Yang et al., 2021). Often, a steep red edge is formed between 680 and 760 nm because of the chlorophyll's substantial absorption of red light and strong reflection of NIR light. Hence, the red edge has a strong spectral response to chlorophyll. The red-edge parameter is one of the most important indicators for crop growth and chlorophyll content estimation (Naguib & Daliman, 2022). The optimum red-edge parameters are then identified by identifying spectral values and chlorophyll content, and a model signifying the relationship between them was developed (Pokhrel et al., 2023).

There are many current techniques to measure chlorophyll content in leaves, which are classified as destructive or non-destructive. The destructive methods, i.e., traditional methods, consist of ultraviolet and visible spectrophotometry, as well as fluorescence analysis, which is used to conduct quantitative chemical analysis of chlorophyll content using the spectral characteristics of the substance (Farag et al., 2022). These methods produce precise results but are time-consuming and labour-intensive, as well as destroying leaves. The soil and plant analysis development (SPAD) method serves as an alternative for ease of use, is low-cost, non-destructive, and enables quick SPAD measurement using light and electricity transmitted through leaves (Zhang et al., 2022). As chlorophyll content corresponds to plant nitrogen status, the SPAD value is used in nitrogen diagnosis to optimise nitrogen application as well as to control diseases, pests, and yield (Wan et al., 2022). A previous study on rice found that SPAD-based nitrogen management can improve grain yield and nitrogen use efficiency, where an increase in grain yield per unit of nitrogen was applied (Hou et al., 2020).

Therefore, the relative leaf chlorophyll content can be detected based on SPAD values, and the results almost resemble chemical experiments, which may replace the traditional chemical approach. The relative chlorophyll content can be detected using a non-damaging and portable chlorophyll metre, namely SPAD-502 chlorophyll metre (SPAD-502, Spectrum

Technologies, Inc., Plainfield, IL, USA) (Kamarianakis & Panagiotakis, 2023). It is one of the fastest and least invasive methods in estimating the relative chlorophyll content of a leaf per square metre, nitrogen content, and NDVI of a paddy crop (Zhang et al., 2021). It utilises the green, red, and NIR wavebands to determine a leaf's chlorophyll content. Hence, the SPAD value is determined by looking at the reflection and absorption of the spectral bands of the crop.

The SPAD readings using the SPAD-502 chlorophyll metre may indicate the growth condition of paddy, with high values indicating healthy plant growth (Guo et al., 2020). The first, second, and third readings can be obtained by fully expanded leaves from the samples (Zhao et al., 2023). Yuan et al. (2016) suggested that the fourth leaf from the top with a 2/3 position distance from the leaf base is suitable for the reading due to low measurement variance in that area. The small samples of SPAD values combined with near-surface UAV remote sensing can be employed on large-scale with high accuracy (Zhang et al., 2019). This approach, however, has limited measuring points and is not suitable for large area measurement, which can be solved by integrating remote sensing and UAV approach (Wang et al., 2022).

There are limitations to using SPAD data to monitor paddy growth because SPAD measurements only provide information on the chlorophyll content of leaves and do not take into account other factors that can affect crop health, such as water stress or disease. Sentinel series satellites' red-edge bands are used to monitor crop chlorophyll content, while sentinel-2 imagery is used to monitor canopy chlorophyll content with high accuracy (Kganyago et al., 2023). Since satellite remote sensing offers large-scale, frequent, low-cost, and massive amounts of information, it has replaced inefficient and costly traditional SPAD monitoring methods.

In other perspectives, the associations between plot-level spectral indices gathered from UAV images and data measured on the ground, such as leaf area index and SPAD values, were calculated and compared. The differences were discussed and analysed at two different paddy growth stages (Duan et al., 2019). By eliminating the backgrounds from the UAV spectral images, Shu et al. (2021) improved the estimation accuracy of SPAD values. The SPAD values were calculated using the cluster-regression method and UAV hyperspectral data (Yang et al., 2021). SPAD measurement offers effective and stable techniques for determining crop phenotyping. SPAD values can be converted to physiological parameters, including leaf chlorophyll content (Wan et al., 2020).

SPAD data has potential with other types of data, such as vegetation indices measurements or weather data of paddy growth. Aerial imagery and object-based image analysis techniques can validate vegetative indices in rice field maps using SPAD data. Normalized Difference Vegetation Index (R=0.957), Normalized Difference Red Edge (NDRE) (R=0.974), Soil Adjusted Vegetation Index (R=0.964), and Optimized Soil

Adjusted Vegetation Index (R=0.966) have proved positive linear correlations with SPAD readings. Vegetation indices showed a higher correlation compared with other vegetation indices, exhibiting a better measure for farmers to make decisions.

Therefore, the optimal combination of feature selection methods (recursive feature elimination, Pearson, and correlation-based feature selection) and machine learning regression models (random forest), elastic net, extreme gradient boosting (XGBoost), and backpropagation neural network with machine learning algorithms can predict SPAD values at individual growth stages and across growth stages of the crop from the images obtained by UAV (Yin et al., 2023). In other words, machine learning regression models (random forest), partial least squares (PLS) regression, deep neural network, and extreme gradient boosting (XGBoost) were used to establish SPAD estimation models. The algorithms such as Findpeaks, successive projections algorithm (SPA), competitive adaptive reweighted sampling, and CARS_SPA were used to extract sensitive characteristic bands that are related to SPAD values (Sudu et al., 2022).

SPAD data are able to develop variable rate application (VRA) maps, which can help farmers apply fertilizers and other inputs more efficiently based on the specific needs of different areas of the field. The NDVI was measured with a GreenSeeker sensor, and SPAD readings were made with a SpadMeter. Geographic coordinates of the NDVI and SPAD measurements were also determined by a global navigation satellite system (GNSS). After applying these fertilization methods, NDVI and SPAD measurements were recorded. Soil and leaf samples were analysed in the laboratory to determine the content of plant nutrients for nitrogen (N), phosphorous (P) and potassium (K). Based on the images generated, NDVI and ground data, including SPAD chlorophyll readings, could have a stronger relationship (Yuhao et al., 2020). The spatial trend that integrates the SPAD chlorophyll map is presented in Figure 6.

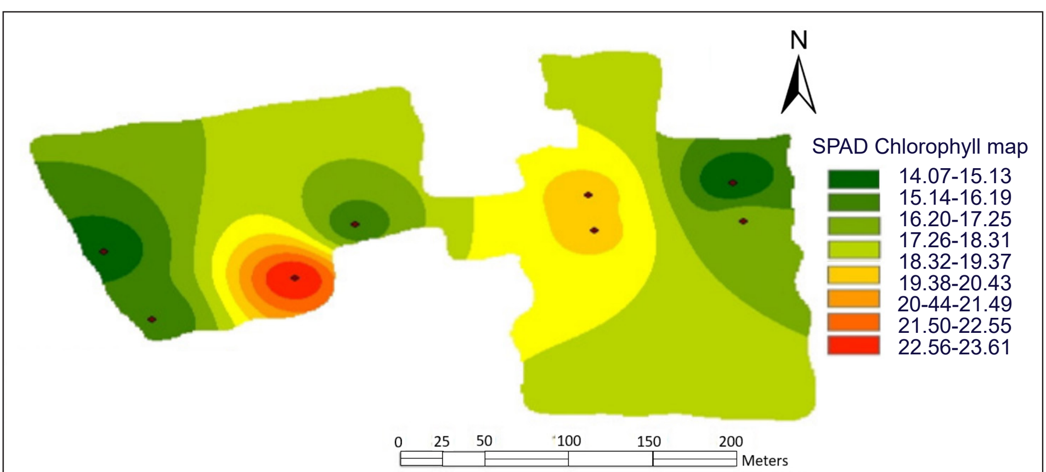

Figure 6. SPAD chlorophyll map for validation of vegetation indices (Yuhao et al., 2020)

IMPLEMENTATION OF PRECISION AGRICULTURE AMONG LOW-INCOME FARMERS

Agriculture digitisation, including precision farming, has changed the way in which food is produced and land is managed. It helps to increase productivity and crop yield, lower expenses incurred for raw materials, and lower the environmental impact of on-farm operations. As the adoption cost of digital farming technology has decreased, remote sensing technologies such as UAVs are now more affordable and accessible, providing an opportunity for low-income farmers in small-scale plantations to improve their livelihood (FAO, 2022). Even if precision farming has significant potential benefits, the adoption of technologies by small-scale farmers and low-resource farming operations needs to be explored further.

One of the potential benefits of UAV usage is the ability to generate high-definition maps from UAV imagery. UAV provides a more accurate and timely representation of small-scale farms than satellite imagery, which often has lower resolution and is subject to cloud presence. It is important because farming operations often have diverse landscapes with a mix of crops, trees, and livestock that the conventional satellite images are unable to accurately represent. Maps and orthomosaics are beneficial for precision agriculture because they allow for a more comprehensive understanding of crop health and distribution (Montilla et al., 2021). Moreover, orthomosaic images can be utilised to monitor changes in the landscape over a specific period, providing useful data to make decisions for farm management. The farmers can evaluate the overall efficacy of their farming practices and identify real-time improvement by utilising orthomosaic images captured from their farms.

The orthomosaic images help them to make a better-informed decision on crop management. They can use this information to adjust their irrigation schedules, fertilisation, and pest control, resulting in increased agricultural productivity and cost savings. Farmers can obtain information on plant health and elevation data, which are generated from UAV images using various software. Also, they can obtain other information such as crop performance, soil moisture, and potential crop yield. It was found that the data helped farmers identify areas in their farms with low yields, thus allowing them to address potential problems in the future.

However, McCarthy et al. (2023) found challenges due to the widespread adoption of UAVs in the agricultural sector. Some farmers have expressed their concern in terms of cost, as well as the data accuracy and analysis. Some farmers remain sceptical about the usefulness of data provided by UAVs, as well as the privacy and security of their personal data. One of the reasons for such scepticism is the farmers' lack of education and literacy, which leads to confusion and mistrust towards technology and regulations (Dhanaraju et al., 2022). Many farmers expressed scepticism about the technology, and most of them were struggling to understand UAV applications and data. The majority of farmers are also reluctant to share their data with government agencies or private companies, and only a small percentage are knowledgeable about UAV regulations and data-sharing laws.

To assist farmers who are less literate with technology, educational materials, training programmes, and community outreach initiatives must be accessible and clear about information on UAV technology, open data, and data privacy regulations. Radio and television, which are used for the dissemination of knowledge, could be an efficient way to reach out to such farmers. Only a small number of farmers have learnt about UAVs from traditional media sources such as print media, radio, or television. Farmers who are aware of UAVs often learn about them from friends and family. So, it is crucial to educate farmers about the benefits of UAV technology and data sharing to increase transparency in data collection and usage through collaboration with local organisations such as non-profit groups and agriculture extension agents.

When information comes from reputable sources such as government agents, educational institutions, and friends/family, it is easier to establish trust (Dhanaraju et al., 2018). Local organisations can help farmers understand the benefits and risks of UAV technology, open data, and data privacy by providing awareness, hands-on training, and dedicated support teams. Both subsistence and commercial farmers are interested in incorporating UAV technology into their farming practices, each with varying interests and concerns in specific applications. Such difference has a significant effect on agricultural policymakers and stakeholders. To encourage the use of UAV technology in agriculture, policies and programmes should take note of the differences and devise strategies to address the needs and concerns of the farmers. Policies that focus on lowering UAV costs or the provision of subsidies, for example, are more effective in persuading commercial farmers to adopt the technology. Programmes that focus on UAV training and education may be better suited for subsistence farmers. Policymakers and stakeholders must tailor their policies and programmes, taking into account their levels of interest, confidence, and perception of UAV technology.

CONCLUSION

UAV technology has the potential to be a powerful tool to capture accurate and high-resolution images for remote sensing data in the future. Farmers may monitor crop development and paddy conditions in real-time using the NDVI map and SPAD data values. Meanwhile, advanced computer vision and machine learning algorithms can be used for image processing. Due to the large amount of data, several machine learning algorithms can be applied to UAV-based multispectral imaging using programming applications such as Python and other related web-based programmed cloud processing should be used in the near future. The analysis output can then be transferred in real-time to automation and robotics for decision-making and quick responses.

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REFERENCES

Abijo, A., Lee, C.-Y., Huang, C.-Y., Ho, P.-C., & Tsai, K.-J. (2023). The beneficial role of photobiomodulation in neurodegenerative diseases. *Biomedicines, 11*(7)*,* 1828-1850. https://doi.org/10.3390/biomedicines11071828

Adnan, N., & Nordin, S. M. (2021). How COVID 19 effect Malaysian paddy industry? Adoption of green fertilizer a potential resolution. *Environment, Development and Sustainability, 23*, 8089-8129. https://doi.org/10.1007/s10668-020-00978-6

Akhtar, R., & Masud, M. M. (2022). Dynamic linkages between climatic variables and agriculture production in Malaysia: a generalized method of moments approach. \ *Environmental Science and Pollution Research, 29*, 41557-41566. https://doi.org/10.1007/s11356-021-18210-x

Ali, I., Cawkwell, F., Dwyer, E., Barrett, B., & Green, S. (2016). Satellite remote sensing of grasslands: From observation to management. *Journal of Plant Ecology, 9*(6), 649-671. https://doi.org/10.1093/jpe/rtw005

Alou, I. N., Steyn, J. M., Annandale, J. G., & Van der Laan, M. (2018). Growth, phenological, and yield response of upland rice (*Oryza sativa* L. cv. Nerica 4®) to water stress during different growth stages. *Agricultural Water Management, 198*, 39-52. https://doi.org/10.1016/j.agwat.2017.12.005

Barbedo, J. G. A. (2019). Detection of nutrition deficiencies in plants using proximal images and machine learning: A review. *Computers and Electronics in Agriculture, 162*, 482-492. https://doi.org/10.1016/j.compag.2019.04.035

Bazezew, M. N., Belay, A. T., Guda, S. T., & Kleinn, C. (2021). Developing maize yield predictive models from sentinel-2 msi derived vegetation indices: an approach to an early warning system on yield fluctuation and food security. *PFG–Journal of Photogrammetry, Remote Sensing and Geoinformation Science, 89*, 535-548. https://doi.org/10.1007/s41064-021-00178-5

Boursianis, A. D., Papadopoulou, M. S., Diamantoulakis, P., Liopa-Tsakalidi, A., Barouchas, P., Salahas, G., Karagiannidisb, G., Wan, S., & Goudos, S. K. (2020). Internet of things (IoT) and agricultural unmanned aerial vehicles (UAVs) in smart farming: A comprehensive review. *Internet of Things, 18*, Article 100187. https://doi.org/10.1016/j.iot.2020.100187

Bujang, A. S., & Bakar, B. H. A. (2019, August). Precision agriculture in Malaysia. In *Proceedings of International Workshop on ICTs for Precision Agriculture* (pp. 6-8). ResearchGate.

Chemura, A., Mutanga, O., & Dube, T. (2017). Integrating age in the detection and mapping of incongruous patches in coffee (Coffea arabica) plantations using multi-temporal Landsat 8 NDVI anomalies. *International Journal of Applied Earth Observation and Geoinformation, 57*, 1-13. https://doi.org/10.1016/j.jag.2016.12.007

Chen, X., Thorp, K. R., Ouyang, Z., Hou, Y., Zhou, B., & Li, Y. (2019). Energy consumption due to groundwater pumping for irrigation in the North China Plain. *Science of The Total Environment, 669*, 1033-1042. https://doi.org/10.1016/j.scitotenv.2019.03.179

Cherlinka, V. (2023). *NDVI FAQ: All you need to know about index*. EOS Data Analytics. https://eos.com/blog/ndvi-faq-all-you-need-to-know-about-ndvi/

Chusnah, W. N., Chu, H. J., Tatas, & Jaelani, L. M. (2023). Machine-learning estimation of high spatiotemporal resolution chlorophyll-a concentration using multi-satellite imagery. *Sustainable Environment Research, 33*(1), Article 11. https://doi.org/10.1186/s42834-023-00170-1

Corti, M., Cavalli, D., Cabassi, G., Vigoni, A., Degano, L., & Gallina, P. M. (2019). Application of a low-cost camera on a UAV to estimate maize nitrogen-related variables. *Precision Agriculture, 20*, 675-696. https://doi.org/10.1007/s11119-018-9609-y

Costa, E. M., Tassinari, W. D. S., Pinheiro, H. S. K., Beutler, S. J., & Dos Anjos, L. H. C. (2018). Mapping soil organic carbon and organic matter fractions by geographically weighted regression. *Journal of Environmental Quality, 47*(4), 718-725. https://doi.org/10.2134/jeq2017.04.0178

Dardak, R. A. (2015). *Transformation of Agricultural Sector in Malaysia through Agricultural Policy*. Malaysian Agricultural Research and Development Institute (MARDI).

Della Chiesa, T., Del Grosso, S. J., Hartman, M. D., Parton, W. J., Echarte, L., Yahdjian, L., & Piñeiro, G. (2022). A novel mechanism to simulate intercropping and relay cropping using the DayCent model. *Ecological Modelling*, *465*, Article 109869. https://doi.org/10.1016/j.ecolmodel.2021.109869

Deng, L., Mao, Z., Li, X., Hu, Z., Duan, F., & Yan, Y. (2018). UAV-based multispectral remote sensing for precision agriculture: A comparison between different cameras. *ISPRS Journal of Photogrammetry and Remote Sensing, 146*, 124-136. https://doi.org/10.1016/j.isprsjprs.2018.09.008

Dhanaraju, M., Chenniappan, P., Ramalingam, K., Pazhanivelan, S., & Kaliaperumal, R. (2022). Smart farming: Internet of Things (IoT)-based sustainable agriculture. *Agriculture, 12*(10), Article 1745. https://doi.org/10.3390/agriculture12101745

Dhau, I., Adam, E., Mutanga, O., & Ayisi, K. K. (2018). Detecting the severity of maize streak virus infestations in maize crop using in situ hyperspectral data. *Transactions of the Royal Society of South Africa, 73*(1), 8-15. https://doi.org/10.1080/0035919X.2017.1370034

Dorairaj, D., & Govender, N. T. (2023). Rice and paddy industry in Malaysia: governance and policies, research trends, technology adoption and resilience. *Frontiers in Sustainable Food Systems, 7*, Article 1093605. https://doi.org/10.3389/fsufs.2023.1093605

Duan, B., Fang, S., Zhu, R., Wu, X., Wang, S., Gong, Y., & Peng, Y. (2019) Remote estimation of rice yield with unmanned aerial vehicle (UAV) data and spectral mixture analysis. *Frontiers Plant Science, 10*, Article 204. https://doi.org/10.3389/fpls.2019.00204

Elfri, M. A. A., Rahman, F. H., Newaz, S. H., Suhaili, W. S., & Au, T. W. (2023). Determining paddy crop health from aerial image using machine learning approach: A Brunei Darussalam based study. In *AIP Conference Proceedings* (Vol. 2643, No. 1). AIP Publishing. https://doi.org/10.1063/5.0113668

Fahmi, Z., Samah, B. A., & Abdullah, H. (2013). Paddy industry and paddy farmers well-being: A success recipe for agriculture industry in Malaysia. *Asian Social Science, 9*(3), Article 177. https://doi.org/10.5539/ass.v9n3p177

FAO. (2022). *Status of Digital Agriculture in 47 Sub-Saharan African Countries*. Food and Agriculture Organization of the United Nations. https://www.fao.org/3/cb7943en/cb7943en.pdf

Farag, M. A., Sheashea, M., Zhao, C., & Maamoun, A. A. (2022). UV fingerprinting approaches for quality control analyses of food and functional food coupled to chemometrics: A comprehensive analysis of novel trends and applications. *Foods, 11*(18), Article 2867. https://doi.org/10.3390/foods11182867

Feng, Z., Song, L., Duan, J., He, L., Zhang, Y., Wei, Y., & Feng, W. (2022). Monitoring wheat powdery mildew based on hyperspectral, thermal infrared, and RGB image data fusion. *Sensors, 22*(1), Article 31. https://doi.org/10.3390/s22010031

Fenghua, Y., Tongyu, X., Yingli, C., Guijun, Y., Wen, D., & Shu, W. (2016). Models for estimating the leaf NDVI of japonica rice on a canopy scale by combining canopy NDVI and multisource environmental data in Northeast China. *International Journal of Agricultural and Biological Engineering, 9*(5), 132-142. https://doi.org/10.3965/j.ijabe.20160905.2266

Firdaus, R. R., Leong Tan, M., Rahmat, S. R., & Senevi Gunaratne, M. (2020). Paddy, rice and food security in Malaysia: A review of climate change impacts. *Cogent Social Sciences, 6*(1), Articlw 1818373. https://doi.org/10.1080/23311886.2020.1818373

Gée, C., Denimal, E., Merienne, J., & Larmure, A. (2021). Evaluation of weed impact on wheat biomass by combining visible imagery with a plant growth model: Towards new non-destructive indicators for weed competition. *Precision Agriculture, 22*, 550-568. https://doi.org/10.1007/s11119-020-09776-6

Gohain, G. B., Singh, K. K., Singh, R. S., Dakhore, K. K., & Ghosh, K. (2022). Application of CERES-sorghum crop simulation model DSSAT v4. 7 for determining crop water stress in crop phenological stages. *Modeling Earth Systems and Environment, 8*, 1963-1975. https://doi.org/10.1007/s40808-021-01194-5

Gracia-Romero, A., Kefauver, S. C., Vergara-Diaz, O., Zaman-Allah, M. A., Prasanna, B. M., Cairns, J. E., & Araus, J. L. (2017). Comparative performance of ground vs. aerially assessed RGB and multispectral indices for early-growth evaluation of maize performance under phosphorus fertilization. *Frontiers in Plant Science, 8*, Article 2004. https://doi.org/10.3389/fpls.2017.02004

Grzebisz, W., & Łukowiak, R. (2021). Nitrogen gap amelioration is a core for sustainable intensification of agriculture - A concept. *Agronomy, 11*(3), Article 419. https://doi.org/10.3390/agronomy11030419

Guo, Y., Chen, S., Li, X., Cunha, M., Jayavelu, S., Cammarano, D., & Fu, Y. (2022). Machine learning-based approaches for predicting SPAD values of maize using multi-spectral images. *Remote Sensing, 14*(6), Article 1337. https://doi.org/10.3390/rs14061337

Guo, Y., Yin, G., Sun, H., Wang, H., Chen, S., Senthilnath, J., Wang, J., & Fu, Y. (2020). Scaling effects on chlorophyll content estimations with RGB camera mounted on a UAV platform using machine-learning methods. *Sensors, 20*(18), Article 5130. http:// doi.org/10.3390/s20185130

Hassan, S. I., Alam, M. M., Illahi, U., Al Ghamdi, M. A., Almotiri, S. H., & Su'ud, M. M. (2021). A systematic review on monitoring and advanced control strategies in smart agriculture. *IEEE Access, 9*, 32517-32548. https://doi.org/10.1109/ACCESS.2021.3057865

Hassler, S. C., & Baysal-Gurel, F. (2019). Unmanned aircraft system (UAS) technology and applications in agriculture. *Agronomy, 9*(10), Article 618. https://doi.org/10.3390/agronomy9100618

Hogan, S., Kelly, N., Stark, B., & Chen, Y. (2017). Unmanned aerial systems for agriculture and natural resources. *California Agriculture, 71*(1), 5-14. https://doi.org/10.3733/ca.2017a0002

Hou, W., Tränkner, M., Lu, J., Yan, J., Huang, S., Ren, T., Cong, R., & Li, X. (2020). Diagnosis of nitrogen nutrition in rice leaves influenced by potassium levels. *Frontiers in Plant Science, 11*, Article 165. https://doi.org/10.3389/fpls.2020.00165

Ibrahim, E. S., Rufin, P., Nill, L., Kamali, B., Nendel, C., & Hostert, P. (2021). Mapping crop types and cropping systems in Nigeria with sentinel-2 imagery. *Remote Sensing, 13*(17), Article 3523. https://doi.org/10.3390/rs13173523

Irmulatov, B. R., Abdullaev, K. K., Komarov, A. A., & Yakushev, V. V. (2021). Prospects for precision management of wheat productivity in the conditions of Northern Kazakhstan. *Agricultural Biology, 56*(1), 92-102. https://doi.org/10.15389/agrobiology.2021.1.92eng

Ishihara, M., Inoue, Y., Ono, K., Shimizu, M., & Matsuura, S. (2015). The impact of sunlight conditions on the consistency of vegetation indices in croplands - Effective usage of vegetation indices from continuous ground-based spectral measurements. *Remote Sensing, 7*(10), 14079-14098. https://doi.org/10.3390/rs71014079

Iwahashi, Y., Sigit, G., Utoyo, B., Lubis, I., Junaedi, A., Trisasongko, B. H., Wijaya, I. M. A. S., Maki, M., Hongo, C., & Homma, K. (2022). Drought damage assessment for crop insurance based on vegetation index by unmanned aerial vehicle (UAV) multispectral images of paddy fields in Indonesia. *Agriculture, 13*(1), Article 113. https://doi.org/10.3390/agriculture13010113

Jamroen, C., Komkum, P., Fongkerd, C., & Krongpha, W. (2020). An intelligent irrigation scheduling system using low-cost wireless sensor network toward sustainable and precision agriculture. *IEEE Access, 8*, 172756-172769. https://doi.org/10.1109/ACCESS.2020.3025590

Janga, B., Asamani, G. P., Sun, Z., & Cristea, N. (2023). A review of practical ai for remote sensing in earth sciences. *Remote Sensing, 15*(16), Article 4112. https://doi.org/10.3390/rs15164112

Kalischuk, M., Paret, M. L., Freeman, J. H., Raj, D., Da Silva, S., Eubanks, S., Wiggins, D. J., Lollar, M., Marois, J. J., Mellinger, H. C., & Das, J. (2019). An improved crop scouting technique incorporating unmanned aerial vehicle–assisted multispectral crop imaging into conventional scouting practice for gummy stem blight in watermelon. *Plant Disease, 103*(7), 1642-1650. https://doi.org/10.1094/PDIS-08-18-1373-RE

Kamarianakis, Z., & Panagiotakis, S. (2023). Design and implementation of a low-cost chlorophyll content meter. *Sensors, 23*(5), Article 2699. https://doi.org/10.3390/s23052699

Karunanithy, K., & Velusamy, B. (2021). Directional antenna based node localization and reliable data collection mechanism using local sink for wireless sensor networks. *Journal of Industrial Information Integration, 24*, Article 100222. https://doi.org/10.1016/j.jii.2021.100222

Kasim, N. M., Ahmad, M. H., Shaharudin, A. B., Naidu, B. M., Chan, Y. Y., & Aris, T. (2018). Food choices among Malaysian adults: Findings from Malaysian adults nutrition survey (MANS) 2003 and MANS 2014. *Malaysian Journal of Nutrition, 24*(1), 63-75.

Kazemi, F., & Parmehr, E. G. (2023). Evaluation of RGB vegetation indices derived from UAV images for rice crop growth monitoring. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 10*, 385-390. https://doi.org/10.5194/isprs-annals-X-4-W1-2022-385-2023

Kganyago, M., Ovakoglou, G., Mhangara, P., Adjorlolo, C., Alexandridis, T., Laneve, G., & Beltran, J. S. (2023). Evaluating the contribution of Sentinel-2 view and illumination geometry to the accuracy of retrieving essential crop parameters. *GIScience & Remote Sensing, 60*(1), Article 2163046. https://doi.org/10.1080/15481603.2022.2163046

Low, J. W., Ortiz, R., Vandamme, E., Andrade, M., Biazin, B., & Grüneberg, W. J. (2020). Nutrient-dense orange-fleshed sweetpotato: Advances in drought-tolerance breeding and understanding of management practices for sustainable next-generation cropping systems in sub-Saharan Africa. *Frontiers in Sustainable Food Systems, 4*, Article 50. https://doi.org/https://doi.org/10.3389/fsufs.2020.00050

Lu, W., Okayama, T., & Komatsuzaki, M. (2021). Rice height monitoring between different estimation models using UAV photogrammetry and multispectral technology. *Remote Sensing, 14*(1), Article 78. https://doi.org/10.3390/rs14010078

Luo, S., Jiang, X., Jiao, W., Yang, K., Li, Y., & Fang, S. (2022). Remotely sensed prediction of rice yield at different growth durations using UAV multispectral imagery. *Agriculture, 12*(9), Article 1447. https://doi.org/10.3390/agriculture12091447

Mallareddy, M., Thirumalaikumar, R., Balasubramanian, P., Naseeruddin, R., Nithya, N., Mariadoss, A., Eazhilkrishna, N., Choudhary, A. K., Deiveegan, M., Subrramanian, E., Padmaja, B., & Vijayakumar, S. (2023). Maximizing water use efficiency in rice farming: A comprehensive review of innovative irrigation management technologies. *Water, 15*(10), Article 1802. https://doi.org/10.3390/w15101802

Mapfumo, R. B., Murwira, A., Masocha, M., & Andriani, R. (2017). Detection of subtle deforestation due to logging using satellite remote sensing in wet and dry savanna woodlands of Southern Africa. *Geocarto International, 32*(5), 514-530. https://doi.org/10.1080/10106049.2016.1161074

McCarthy, C., Nyoni, Y., Kachamba, D. J., Banda, L. B., Moyo, B., Chisambi, C., Banfill, J., & Hoshino, B. (2023). Can drones help smallholder farmers improve agriculture efficiencies and reduce food insecurity in Sub-Saharan Africa? Local perceptions from Malawi. *Agriculture, 13*(5), Article 1075. https://doi.org/10.3390/agriculture13051075

McCarty, J. L., Neigh, C. S. R., Carroll, M. L., & Wooten, M. R. (2017). Extracting smallholder cropped area in Tigray, Ethiopia with wall-to-wall sub-meter WorldView and moderate resolution Landsat 8 imagery. *Remote Sensing of Environment, 202*, 142-151. https://doi.org/10.1016/j.rse.2017.06.040

Meroni, M., d'Andrimont, R., Vrieling, A., Fasbender, D., Lemoine, G., Rembold, F., Seguini, L., & Verhegghen, A. (2021). Comparing land surface phenology of major European crops as derived from SAR and multispectral data of Sentinel-1 and-2. *Remote Sensing of Environment, 253*, Article 112232. https://doi.org/10.1016/j.rse.2020.112232

Ministry of Agiculture. (1984). *Third National Agricultural Policy (1998 - 2010) - Executive Summary*. https://www.pmo.gov.my/dokumenattached/Dasar/29THIRD_NATIONAL_AGRICULTURAL_POLICY_(1998_-_2010)_-_EXECUTIVE_SUMMARY.pdf

Ministry of Agriculture (2016). *Dasar Sekuriti Makanan Negara* [National Food Security Policy]. Ministry of Agriculture and Agro-based Industry. https://www.kpkm.gov.my/

Monteiro, A., Santos, S., & Gonçalves, P. (2021). Precision agriculture for crop and livestock farming - Brief review. *Animals, 11*(8), Article 2345. https://doi.org/10.3390/ani11082345

Montilla, R., Montilla, G., Perez, E., Frassato, L., & Seijas, C. (2021). Precision agriculture for rice crops with an emphasis in low health index areas. *Revista Facultad Nacional de Agronomía Medellín, 74*(1), 9383-9393. https://doi.org/10.15446/rfnam.v74n1.85310

Munnaf, M. A., Haesaert, G., Van Meirvenne, M., & Mouazen, A. M. (2020). Site-specific seeding using multi-sensor and data fusion techniques: A review. *Advances in Agronomy, 161*, 241-323. https://doi.org/10.1016/bs.agron.2019.08.001

Naguib, N. S., & Daliman, S. (2022, November). Analysis of NDVI and NDRE indices using satellite images for crop identification at Kelantan. In *IOP Conference Series: Earth and Environmental Science* (Vol. 1102, No. 1, p. 012054). IOP Publishing. https://doi.org/10.1088/1755-1315/1102/1/012054

Nestel, D., Cohen, Y., Shaked, B., Alchanatis, V., Nemny-Lavy, E., Miranda, M. A., Sciarretta, A., & Papadopoulos, N. T. (2019). An integrated decision support system for environmentally-friendly management of the Ethiopian fruit fly in greenhouse crops. *Agronomy, 9*(8), Article 459. https://doi.org/10.3390/agronomy9080459

Neupane, K., & Baysal-Gurel, F. (2021). Automatic identification and monitoring of plant diseases using unmanned aerial vehicles: A review. *Remote Sensing, 13*(19), Article 3841. https://doi.org/10.3390/rs13193841

Nguy-Robertson, A., Gitelson, A., Peng, Y., Viña, A., Arkebauer, T., & Rundquist, D. (2012). Green leaf area index estimation in maize and soybean: Combining vegetation indices to achieve maximal sensitivity. *Agronomy Journal Abstract – Biometry, Modeling and Statistics, 104*(5), 1336-1347. https://doi.org/10.2134/agronj2012.0065

Norasma, C. Y. N., Fadzilah, M. A., Roslin, N. A., Zanariah, Z. W. N., Tarmidi, Z., & Candra, F. S. (2019, April). Unmanned aerial vehicle applications in agriculture. In *IOP Conference Series: Materials Science and Engineering* (Vol. 506, p. 012063). IOP Publishing. https://doi.org/10.1088/1757-899X/506/1/012063

Olson, D., & Anderson, J. (2021). Review on unmanned aerial vehicles, remote sensors, imagery processing, and their applications in agriculture. *Agronomy Journal, 113*(2), 971-992. https://doi.org/10.1002/agj2.20595

Omar, S. C., Shaharudin, A., & Tumin, S. A. (2019). *The Status of the Paddy and Rice Industry in Malaysia*. Khazanah Research Institute. https://www.krinstitute.org/assets/contentMS/img/template/editor/Rice%20Report_Ppt%20Slide_Sarena.pdf

Onyango, C. M., Nyaga, J. M., Wetterlind, J., Söderström, M., & Piikki, K. (2021). Precision agriculture for resource use efficiency in smallholder farming systems in Sub-Saharan Africa: A systematic review. *Sustainability, 13*(3), Article 1158. https://doi.org/10.3390/su13031158

Osman, Z., & Shahiri, H. (2017). Ethnic and gender inequality in employment during the new economic policy. *Institutions and Economies, 6*(1), 57-72.

Othman, K., Omar, H., Fuad, H. A., Laidin, J., & Ramli, I. M. (2020). The causal impact of government support on the small strategic crop industry: Malaysia's experience. *Asian Journal of Agriculture and Rural Development, 10*(1), 298-310. https://doi.org/10.18488/journal.1005/2020.10.1/1005.1.298.310

Pérez-Ortiz, M., Gutiérrez, P. A., Peña, J. M., Torres-Sánchez, J., López-Granados, F., & Hervás-Martínez, C. (2016). Machine learning paradigms for weed mapping via unmanned aerial vehicles. In *2016 IEEE symposium series on computational intelligence (SSCI)* (pp. 1-8). IEEE Publication. https://doi.org/10.1109/SSCI.2016.7849987

Pokhrel, A., Virk, S., Snider, J. L., Vellidis, G., Hand, L. C., Sintim, H. Y., Parkash, V., Chalise, D. P., Lee, J. M., & Byers, C. (2023). Estimating yield-contributing physiological parameters of cotton using UAV-based imagery. *Frontiers in Plant Science, 14*. https://doi.org/10.3389%2Ffpls.2023.1248152

Ponnusamy, V., & Natarajan, S. (2021). Precision agriculture using advanced technology of IoT, unmanned aerial vehicle, augmented reality, and machine learning. In D. Gupta, C. Hugo, de Albuquerque, A. Khanna & P. L. Mehta, (Eds.), *Smart Sensors for Industrial Internet of Things* (pp. 207-229). Springer. https://doi.org/10.1007/978-3-030-52624-5_14

Pretorius, Z. A., Lan, C. X., Prins, R., Knight, V., McLaren, N. W., Singh, R. P., Bender, C. M., & Kloppers, F. J. (2017). Application of remote sensing to identify adult plant resistance loci to stripe rust in two bread wheat mapping populations. *Precision Agriculture, 18*, 411-428. https://doi.org/10.1007/s11119-016-9461-x

Raddi, S., Giannetti, F., Martini, S., Farinella, F., Chirici, G., Tani, A., Maltoni, A., & Mariotti, B. (2022). Monitoring drought response and chlorophyll content in Quercus by consumer-grade, near-infrared (NIR) camera: A comparison with reflectance spectroscopy. *New Forests, 53*(2), 241-265. https://doi.org/10.1007/s11056-021-09848-z

Rahmat, S. R., Firdaus, R. R., Mohamad Shaharudin, S., & Yee Ling, L. (2019). Leading key players and support system in Malaysian paddy production chain. *Cogent Food & Agriculture, 5*(1), Article 1708682. https://doi.org/10.1080/23311932.2019.1708682

Ramli, N. N., Shamsudin, M. N., Mohamed, Z., & Radam, A. (2012). The impact of fertilizer subsidy on Malaysia paddy/rice industry using a system dynamics approach. *International Journal of Social Science and Humanity, 2*(3), Article 213.

Richard, K., Abdel-Rahman, E. M., Subramanian, S., Nyasani, J. O., Thiel, M., Jozani, H., Borgemeister, C., & Landmann, T. (2017). Maize cropping systems mapping using rapideye observations in agro-ecological landscapes in Kenya. *Sensors, 17*(11), Article 2537. https://doi.org/10.3390/s17112537

Roman, A., & Ursu, T. (2016). Multispectral satellite imagery and airborne laser scanning techniques for the detection of archaeological vegetation marks. In C. H. Opreanu & V. A. Lazarecu (Eds.), *Landscape Archaeology on the Northern Frontier of the Roman Empire at Porolissum: An Interdisciplinary Research Project* (pp. 141-152). Mega Publishing House.

Rosle, R., Che'Ya, N. N., Roslin, N. A., Halip, R. M., & Ismail, M. R. (2019). Monitoring early stage of rice crops growth using normalized difference vegetation index generated from UAV. In *IOP Conference Series: Earth and Environmental Science* (Vol. 355, No. 1, p. 012066). IOP Publishing. https://doi.org/10.1088/1755-1315/355/1/012066

Rosle, R., Sulaiman, N., Che′ Ya, N. N., Radzi, M. F. M., Omar, M. H., Berahim, Z., Ilahi, W. F. F., Shah, J. A., & Ismail, M. R. (2022). Weed detection in rice fields using UAV and multispectral aerial imagery. *Chemistry Proceedings, 10*(1), Article 44. https://doi.org/10.3390/IOCAG2022-12519

Roth, L., Barendregt, C., Bétrix, C. A., Hund, A., & Walter, A. (2022). High-throughput field phenotyping of soybean: Spotting an ideotype. *Remote Sensing of Environment, 269*, Article 112797. https://doi.org/10.1016/j.rse.2021.112797

Rusli, N. M., Noor, Z. Z., & Taib, S. M. (2024). Life cycle assessment of rice production in Muda Granary Area, Kedah, Malaysia. *Journal of Advanced Research in Applied Sciences and Engineering Technology, 35*(2), 69-83. https://doi.org/10.37934/araset.35.2.6983

Sari, M. Y. A., Hassim, Y. M. M., Hidayat, R., & Ahmad, A. (2021). Monitoring rice crop and paddy field condition using UAV RGB imagery. *International Journal on Informatics Visualization, 5*(4), 469-474. https://dx.doi.org/10.30630/joiv.5.4.742

Sato, N. K., Tsuji, T., Iijima, Y., Sekiya, N., & Watanabe, K. (2023). Predicting rice lodging risk from the distribution of available nitrogen in soil using uas images in a paddy field. *Sensors, 23*(14), Article 6466. https://doi.org/10.3390/s23146466

Seglah, P. A., Wang, Y., Wang, H., Bi, Y., Zhou, K., Wang, Y., Wang, Y., Wang, H., & Feng, X. (2020). Crop straw utilization and field burning in Northern region of Ghana. *Journal of Cleaner Production, 261*, Article 121191. https://doi.org/10.1016/j.jclepro.2020.121191

Sharabiani, V. R., Nazarloo, A. S., Taghinezhad, E., Veza, I., Szumny, A., & Figiel, A. (2023). Prediction of winter wheat leaf chlorophyll content based on VIS/NIR spectroscopy using ANN and PLSR. *Food Science & Nutrition, 11*(5), 2166-2175. https://doi.org/10.1002/fsn3.3071

Shu, M., Zuo, J., Shen, M., Yin, P., Wang, M., Yang, X., Tang, J., Li, B., & Ma, Y. (2021). Improving the estimation accuracy of SPAD values for maize leaves by removing UAV hyperspectral image backgrounds. *International Journal of Remote Sensing, 42*, 5862-5881. https://doi.org/10.1080/01431161.2021.1931539

Sishodia, R. P., Ray, R. L., & Singh, S. K. (2020). Applications of remote sensing in precision agriculture: A review. *Remote Sensing, 12*(19), Article 3136. https://doi.org/10.3390/rs12193136

Souza, F. H. Q., Martins, P. H. A., Martins, T. H. D., Teodoro, P. E., & Baio, F. H. R. (2020). The use of vegetation index via remote sensing allows estimation of soybean application rate. *Remote Sensing Applications: Society and Environment, 17*, Article 100279. https://doi.org/10.1016/j.rsase.2019.100279

Stöcker, C., Bennett, R., Nex, F., Gerke, M., & Zevenbergen, J. (2017). Review of the current state of UAV regulations. *Remote Sensing, 9*(5), Article 459. https://doi.org/10.3390/rs9050459

Sudu, B., Rong, G., Guga, S., Li, K., Zhi, F., Guo, Y., Zhang, J., & Bao, Y. (2022). Retrieving SPAD values of summer maize using UAV hyperspectral data based on multiple machine learning algorithm. *Remote Sensing, 14*(21), Article 5407. https://doi.org/10.3390/rs14215407

Sui, Y. Y., Wang, Q. Y., & Yu, H. Y. (2016). Prediction of greenhouse cucumber disease based on chlorophyll fluorescence spectrum index. *Guang pu xue yu Guang pu fen xi= Guang pu, 36*(6), 1779-1782.

Takoutsing, B., Martín, J. A. R., Weber, J. C., Shepherd, K., Sila, A., & Tondoh, J. (2017). Landscape approach to assess key soil functional properties in the highlands of Cameroon: Repercussions of spatial relationships for land management interventions. *Journal of Geochemical Exploration, 178*, 35-44. https://doi.org/10.1016/j.gexplo.2017.03.014

The Star. (2019, April 13). Where does Malaysia's paddy and rice industry stand? *The Star*. https://www.thestar.com.my/business/business-news/2019/04/13/where-does-malaysias-paddy-and-rice-industry-stand/

Tsai, D. M., & Chen, W. L. (2017). Coffee plantation area recognition in satellite images using Fourier transform. *Computers and Electronics in Agriculture, 135*, 115-127. https://doi.org/10.1016/j.compag.2016.12.020

Tsouros, D. C., Bibi, S., & Sarigiannidis, P. G. (2019). A review on UAV-based applications for precision agriculture. *Information, 10*(11), Article 349. https://doi.org/10.3390/info10110349

USDA. (2020). *World Agricultural Production*. USDA Foreign Agricultural Service, USA. https://www.fas.usda.gov/data/world-agricultural-production

Wan, L., Cen, H., Zhu, J., Zhang, J., Zhu, Y., Sun, D., Du, X., Zhai, L., Weng, H., Li, Y., Li, X., Bao, Y., Shou, J., & He, Y. (2020). Grain yield prediction of rice using multi-temporal UAV-based RGB and multispectral images and model transfer - A case study of small farmlands in the South of China. *Agricultural and Forest Meteorology, 291*, Article 108096. https://doi.org/10.1016/j.agrformet.2020.108096

Wan, W., Zhao, Y., Xu, J., Liu, K., Guan, S., Chai, Y., Cui, H., Wu, P., & Diao, M. (2022). Reducing and delaying nitrogen recommended by leaf critical SPAD value was more suitable for nitrogen utilization of spring wheat under a new type of drip-irrigated system. *Agronomy, 12*(10), Article 2331. https://doi.org/10.3390/agronomy12102331

Wang, K., Huggins, D. R., & Tao, H. (2019). Rapid mapping of winter wheat yield, protein, and nitrogen uptake using remote and proximal sensing. *International Journal of Applied Earth Observation and Geoinformation, 82*, Article 101921. https://doi.org/10.1016/j.jag.2019.101921

Wang, Y. P., Chang, Y. C., & Shen, Y. (2022). Estimation of nitrogen status of paddy rice at vegetative phase using unmanned aerial vehicle based multispectral imagery. *Precision Agriculture, 23*(1), 1-17. https://doi.org/10.1007/s11119-021-09823-w

Winowiecki, L. A., Vågen, T. G., Boeckx, P., & Dungait, J. A. (2017). Landscape-scale assessments of stable carbon isotopes in soil under diverse vegetation classes in East Africa: Application of near-infrared spectroscopy. *Plant and Soil, 421*, 259-272. https://doi.org/10.1007/s11104-017-3418-3

Xie, C., & Yang, C. (2020). A review on plant high-throughput phenotyping traits using UAV-based sensors. *Computers and Electronics in Agriculture, 178*, Article 105731. https://doi.org/10.1016/j.compag.2020.105731

Yang, X., Yang, R., Ye, Y., Yuan, Z., Wang, D., & Hua, K. (2021). Winter wheat SPAD estimation from UAV hyperspectral data using cluster-regression methods. *International Journal of Applied Earth Observation and Geoinformation, 105*, Article 102618. https://doi.org/10.1016/j.jag.2021.102618

Yin, Q., Zhang, Y., Li, W., Wang, J., Wang, W., Ahmad, I., Zhou, G., & Huo, Z. (2023). Estimation of winter wheat SPAD values based on UAV multispectral remote sensing. *Remote Sensing, 15*(14), Article 3595. https://doi.org/10.3390/rs15143595

Yuan, Z., Cao, Q., Zhang, K., Ata-Ul-Karim, S. T., Tian, Y., Zhu, Y., Cao, W., & Liu, X. (2016). Optimal leaf positions for SPAD meter measurement in rice. *Frontiers in plant science, 7*, Article 719. https://doi.org/10.3389/fpls.2016.00719

Yuhao, A., Che'Ya, N. N., Roslin, N. A., & Ismail, M. R. (2020). Rice chlorophyll content monitoring using vegetation indices from multispectral aerial imagery. *Pertanika Journal of Science & Technology*, *28*(3), 779-795.

Zhang, K., Liu, X., Ma, Y., Wang, Y., Cao, Q., Zhu, Y., Cao, W., & Tian, Y. (2021). A new canopy chlorophyll index-based paddy rice critical nitrogen dilution curve in eastern China. *Field Crops Research, 266*, Article 108139. https://doi.org/10.1016/j.fcr.2021.108139

Zhang, R., Yang, P., Liu, S., Wang, C., & Liu, J. (2022). Evaluation of the methods for estimating leaf chlorophyll content with SPAD chlorophyll meters. *Remote Sensing, 14*(20), Article 5144. https://doi.org/10.3390/rs14205144

Zhang, S., Zhao, G., Lang, K., Su, B., Chen, X., Xi, X., & Zhang, H. (2019) Integrated satellite, unmanned aerial vehicle (UAV) and ground inversion of the SPAD of winter wheat in the reviving stage. *Sensors, 19*(17), Article 1485. http://doi.org/10.3390/s19071485

Zhang, Z., & Zhu, L. (2023). A review on unmanned aerial vehicle remote sensing: platforms, sensors, data processing methods, and applications. *Drones, 7*(6), Article 398. https://doi.org/10.3390/drones7060398

Zhao, Y., Yang, P., Cheng, Y., Liu, Y., Yang, Y., & Liu, Z. (2023). Insights into the physiological, molecular, and genetic regulators of albinism in Camellia sinensis leaves. *Frontiers in Genetics, 14*. https://doi.org/10.3389%2Ffgene.2023.1219335

Zhu, W., Feng, Z., Dai, S., Zhang, P., & Wei, X. (2022). Using UAV multispectral remote sensing with appropriate spatial resolution and machine learning to monitor wheat scab. *Agriculture*, *12*(11), Article 1785. https://doi.org/10.3390/agriculture12111785