*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

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 Granary | 2016 | | 2017 | | 2018 | | 2019 | | 2020 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 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.* htttps://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.
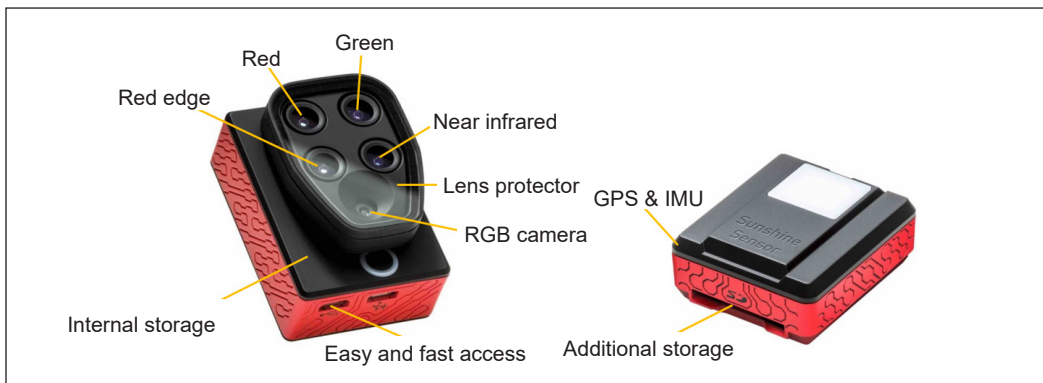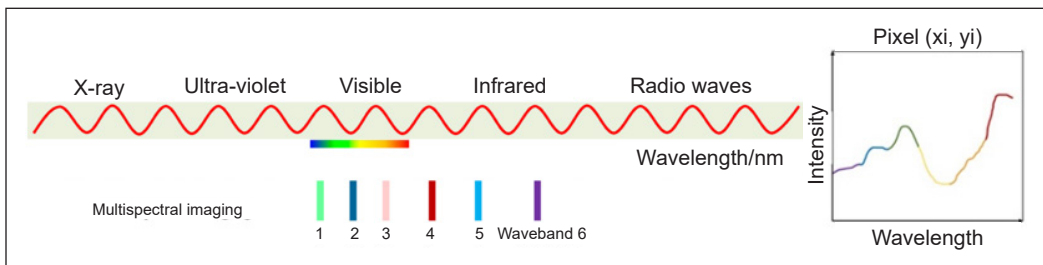
*Figure 1.* Multispectral sensor



*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



*Figure 3.* MicaSense-RedEdge-MX multispectral sensor

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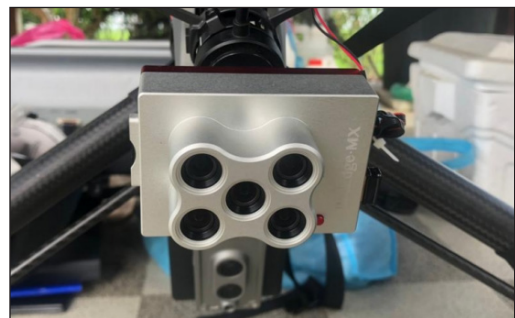
Multispectral imagery consists of 3−10 distinguished "wider" bands. The images produced can be further analysed with GIS or RS software. Norasma et al. (2019) used a MicaSense sensor to create the rice growth map. This sensor is also used by Jiang et al.

(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
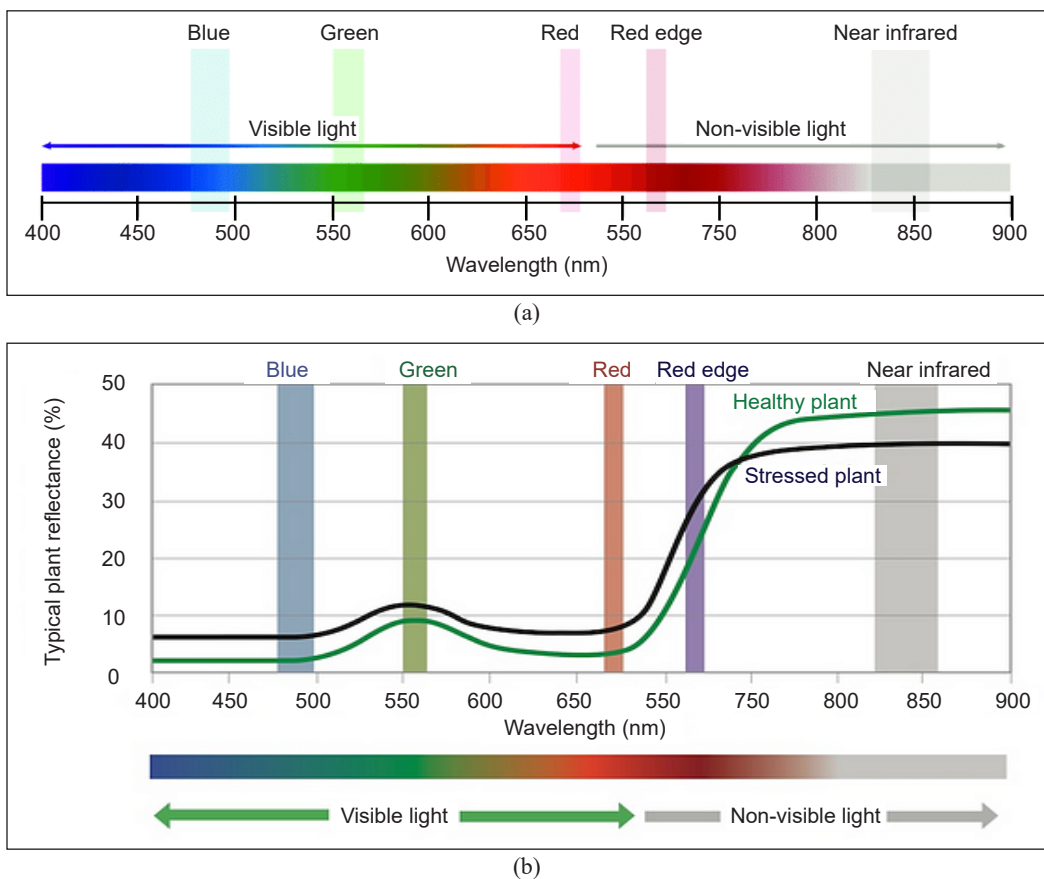


(a)



(b)

*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:

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

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:

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

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:

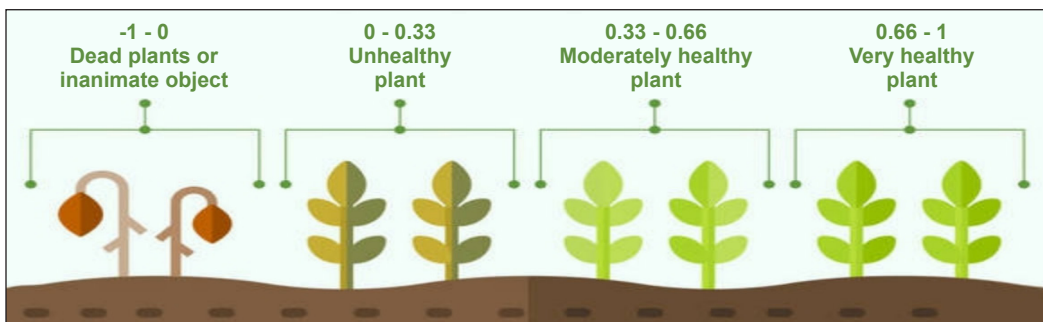$$((NIR - R) / (NIR + R + L)) * (1 + L) \tag{3}$$



*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.
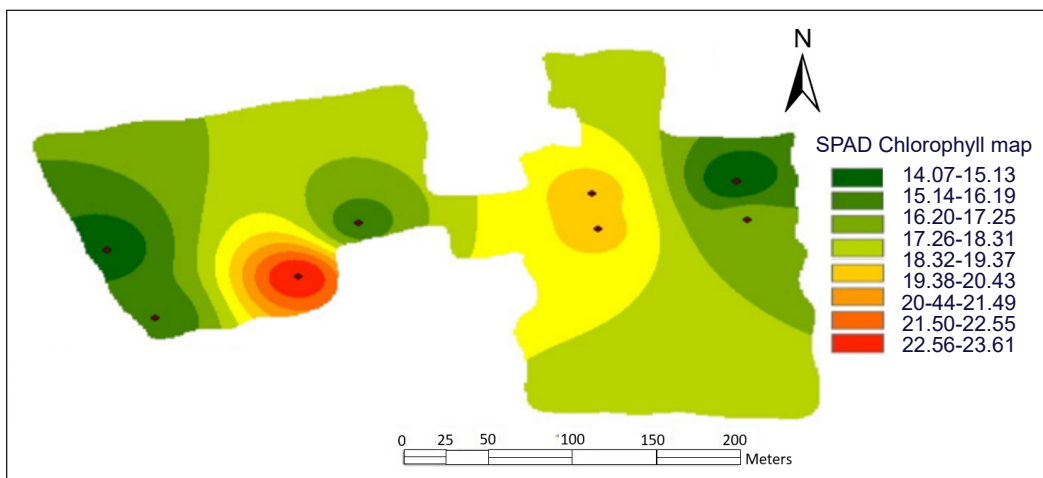


*Figure 6.* SPAD chlorophyll map for validation of vegetation indices (Yuhao et al., 2020)

## 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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