WEED DETECTION IN RICE FIELD USING UAV AND MULTISPECTRAL AERIAL IMAGERY

Weed Detection in Rice Field Using UAV and Multispectral Aerial Imagery

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ABSTRACT

Weeds are plants that compete for nutrients, space, light and exert many harmful effects by reducing the quality and quantity of crops if the weed population is uncontrolled. The direct yield loss was estimated within the range of 16-86% depending on the type of rice culture, weed species, and environmental conditions. Currently, farmers apply herbicides at the same rate to control weeds. Excessive chemical usage will negatively affect the environment, crop productivity, and the economy. A map-based system can help in directing the herbicide sprayer to specific areas. Producing a weed map is very challenging due to the similarity of the crops and the weeds. Therefore, using UAV and multispectral imagery will solve the weed detection problem in the paddy field. The objective of this study project is to detect weeds in the rice field using UAV and multispectral imagery. Multispectral imagery was used to identify the condition of the crops. It can be an indicator to determine weeds and paddy plants based on the spectral resolution in the imagery. This study was done at Tunjang, Jitra, Kedah with a total area of 0.5 ha. Two types of data collections were ground data and aerial data collection. Ground data were collected using the Soil Plant Analysis Development (SPAD) meter, which can read the chlorophyll value of the area. For aerial data, the unmanned aerial vehicle (UAV), attached with the multispectral camera, Micasense, and Red Green Blue (RGB) camera. Aerial data collection was collected on the same day as ground data collection on 30th June 2020 (the day after sowing (DAS) 34). Correlation between those two data was made. The study output was a weed map developed from the RGB image and multispectral imagery normalized difference vegetation index (NDVI) map. The correlation of the NDVI value from the UAV with SPAD data was weak. It has a positive but no significant value at the 0.05 level (2 tail).

Keywords: Multispectral Imagery, Rice Plant, UAV, Weed

1.0 INTRODUCTION

Weeds are undesirable plants that develop within the field, which will compete with crops for soil nutrients, water, space, canopy, and light (Fernández-Aparicio, 2016). Weeds can have a few negative results, such as crop yield misfortune, production of a massive number of seeds in this manner, making a weed seed bank within the field, and contamination of grain during harvesting if left unchecked (Sivakumar et al., 2020). Weeds can also introduce diseases that can cause yield loss (Kawamura et al., 2020). Therefore, weed management is critical for agricultural production (Liu & Bruch, 2020). Weed competition is one of the significant causes of yield loss (Manisankar et al., 2020). This is because it will disrupt the growth of paddy by competing with the crops for water, light, nutrients, and space (Sivakumar et al., 2020). Weeds can also increase production costs, trouble harvesting, deterioration of product quality, increment risk of pests and infections, and diminish in cultivated areas' commercial value (dos Santos Ferreira et al., 2017). If the rice field is heavily infested with weeds, the yield drop is significant (Jabran et al., 2018; Roslin et al., 2021). The direct yield loss was estimated within the range of 16-86% depending on type of rice culture, cultivar, weed species and density, cropping season, plant spacing, fertilizer rate, duration and time of weed infestation, and climatic and environmental conditions (Garg & Tiwari, 2019).

Weeds management are highly reliant on herbicides; however, other control measures are integrated, including cultural, physical, biological, and mechanical methods (Dilipkumar et al., 2017). In Malaysia, weed management is mostly herbicide-based and costs around RM17.03 million annually on herbicides for rice alone (Rao, A. N., & Wani, S. P. 2015) and total of yield losses ranging from 10% to 35% have been recorded. Therefore, if not tested, the weedy rice infestations also might reduce harvests by 80% (Roslin et al., 2021). Weeds' spatial density is not uniform over the field, thereby driving the abuse of chemicals in natural concerns and the advancement of herbicide-resistant weeds (Giacomo & David, 2017).

Therefore, technological advancement has a significant impact on the efficiency of weed management, such as the application of unmanned aerial vehicles (UAV) and satellite imagery, which has brought a colossal effect on-farm management. (Pádua et al., 2017). UAVs can produce aerial images implanted with different data depending on sensors utilized, such as multispectral camera, RGB camera, hyperspectral camera, and thermal sensor. UAVs provide the capacity to cover large zones in a brief sum of time and payload capacity to carry optical sensors (Sivakumar et al., 2020). These images from the UAV and sensors will later undergo processing to form an important detail that is understandable for the end-users. A map-based system created from the UAV images can help direct the herbicide sprayer to specific areas to overcome this. Producing a weed map is very challenging due to the similarity of the crops and the weeds. Therefore, UAV and multispectral imagery will solve the weed practice application and the yield. This study aimed to detect weeds in rice fields using remote sensing multispectral imagery.

2.0 UNMANNED AERIAL VEHICLE (UAV) AND WEED DETECTION USING MULTISPECTRAL IMAGERY

Unmanned aerial vehicle (UAV) remote sensing systems have become a popular topic worldwide because they are mobile, rapid, and economic (Yang et al., 2017). Moreover, it has potential as an alternative given its low cost of operation in environmental monitoring and agriculture application (Yang et al., 2017). Drone imagery is valuable information in giving an exact estimate of loss (Giacomo & David, 2017). In this case, the drone images can produce a weed map. Weeding imagery, timely weed detection and rice or weed discrimination, can decrease the weeding cost process (Kawamura et al., 2020).

Images acquired by Unmanned Aerial Vehicles (UAV) have proven their suitability for early weed detection in crops (de Castro et al., 2018). Remote sensing with unmanned aerial vehicles (UAV) is considered a game-changer in precision farming because it offers a phenomenal spectral, spatial, and temporal resolution. Still, it can moreover give point by point vegetation stature information and multiangular perceptions (Maes & Steppe, 2019). The UAV can be effectively flown and maintained with small training, making it an excellent alternative for farmers looking to progress their farming by merging agriculture with remote sensing technology (Cano et al., 2017). Therefore, UAV use will allow farmers to monitor their crop condition continually and compare the ground surveying for the validation process in an effective way (Norasma et al., 2018). Table 1 shows the advantages and limitations of different types of UAVs.

Table 1: Advantages and Limitations of Different Types of UAV

Type of UAV	Advantages	Disadvantages	Sources
Fixed-wing	• Simpler structure • Longer flight duration at higher speed • Larger area coverage per flight • Lower power consumption	• Low-resolution image • Not able to hover • Require specific runways	(Gago et al., 2015; Senthilnath et al., 2017; Shi et al., 2016)
Rotary wing	• Able to fly and land vertically • Their capacity to hover and perform agile manoeuvring • It is fully automated, which allows the drone to start and end at the launch point • High-resolution image	• Lower flight duration • Low payload capacity • Lower flight speed • Restricted area coverage per flight	

Weed management is one of the principal vital aspects of crop productivity, and finding its exact location has become a problem for farmers for several decades (Osorio et al., 2020). Therefore, particular weed treatment is essential in crop management related to crop health and yield (Sa et al., 2018). However, a key challenge is solid and precise weed location to lower the risk of harm to surrounding plants (Sa et al., 2018). According to Pena et al. (2013) and Osorio et al. (2020), because the crop plants are small and have several traits that are similar to weeds, detecting them may be challenging. As a result, satellite photos are unable to give the necessary data. Unmanned aircraft systems (UASs) are a better option because they can be controlled remotely or automatically over short and long distances, capturing digital images at the height and frequency specified by the user, which varies depending on the type of UAV (unmanned aerial vehicle) that operates the system.

These UAVs can also be equipped with multispectral cameras, which provide more information than an RGB digital image because they record spectral bands not visible to the human eye, such as near infrared (NIR), and provide data on things like visible light reflectance and vegetation indices (Osorio et al., 2020). Multispectral imaging initiated by sensors that compute reflected energy within several specific sections or recognized as bands of the electromagnetic spectrum and utilized about tens of discrete spectral bands for image processing (Roslim et al., 2021). This multispectral image can be taken from a UAV at usually 60 and 70 m height, depending on the type of crops and location (Barrero & Perdomo, 2018). These images can later be processed using software such as ArcGIS to determine the exact spot of weed within the area. Therefore, this technology can help farmers overcome their weed problem on the field.

2.1 Spectral Reflectance of Vegetation and Vegetation Index

To detect and map weeds using remote sensing technologies, spectral reflectance differences between weeds and their surroundings must be identify, and the spatial and spectral resolution of remote sensing equipment must be sufficient to detect these differences (Gibson et al., 2004). Each object, such as plant, soil, and water, will have a distinctive reflection rate and absorption of light energy radiated from the sun. Remote sensing can recognise the interactions between reflected, absorbed, and transmitted energy. This relationship between reflected, interested, and transmitted power can be utilized to decide the spectral signatures of individual plants. Every plant has a unique spectral signature. However, spectral reflectance curve design for each distinctive plant may have a comparable graph pattern across visible spectrum till near-infrared. Figure 1 shows the vegetative spectral reflectance curve (Kamal et al., 2017).

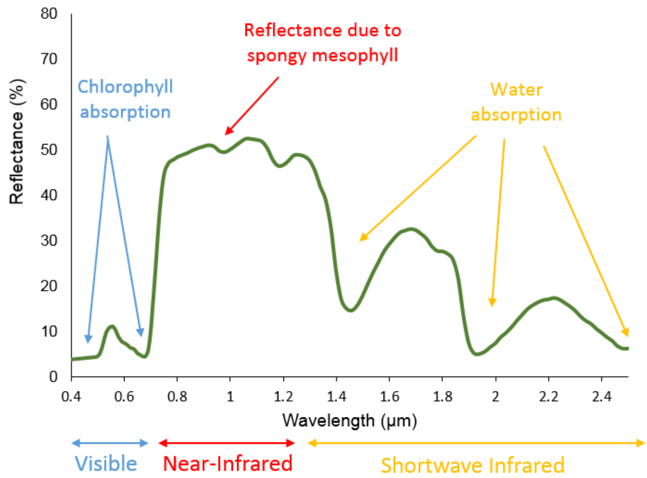

Figure 1: vegetative spectral reflectance curve (Kamal et al., 2017)

The majority of the plant assimilate blue and red bands and reflect green bands and NIR. The comparison or relationship between these reflectance values at distinctive wavelengths is called a vegetative index is commonly utilized to decide plant vigor. The most common vegetative index is the normalized difference vegetative index (NDVI). NDVI is one example of an index and can act as an indicator of plant vigor (Kumar et al, 2015). NDVI is used to determine the amount of vegetation in an area. NDVI compares the reflectance values of the red and NIR regions of the electromagnetic spectrum. The green leaves strongly absorb visible light (red wavelength) but highly reflect near-infrared wavelength (Honrado et al., 2017). This study has shown that NDVI can analyse any vegetative crops, and it is also closely related to SPAD value. The equation for the NDVI

$$NDVI = (NIR - R)/(NIR+R) \quad \text{Eq. 1}$$

Where,

NIR represent the reflectance value of the near-infrared band,
R is the reflectance value in the red band (Vergara-Díaz et al., 2016).
NDVI create a value range from +1.0 to -1.0. High vegetation value will be within the field near 1.0, whereas the lowest vegetation value will be within the range near 0 (Mahlein, 2016).

3.0 MATERIAL AND METHOD

The study area for the project was in Lembaga Kemajuan Pertanian Muda MADA, Tunjang, Jitra, Kedah. The rice variety utilized in this study plot was PadiU Putra. The PadiU Putra seeds were broadcasted and planted on 28th May 2020. The total area used for this project was 0.5 ha. The first data acquisition for this project was done on 15th June 2020 (the day after sowing (DAS) 19) and the second one on 23rd June 2020 (DAS 27).

3.1 Data Collections

3.1.1 Experimental Design

A total of 8 blocks were made from the study plot area. Two treatments were used and labeled T0 and T1, which indicates control and fertilizer and herbicide, respectively. Eight random units were taken from each block for SPAD meter reading as ground data. So, there will be 64 points because there were eight blocks with four replication and two types of treatment, hence the eight blocks of the complete experimental design we made.

3.1.2 Ground and Aerial Imagery Data Collection

The data collection was taken on 30th June 2020 (the day after sowing (DAS) 34). One quadrant of 0.5 x 0.5 m was used to take the randomly sampled data throughout the plots. The physiological data collection for each plot was the relative chlorophyll content (SPAD unit), weeds and paddy (Figure 2). The tool used for this data collection was the SPAD Meter; SPAD 502 Plus Chlorophyll Meter.

Figure 2: SPAD 502 Plus Chlorophyl Meter (Mohd Firdaus, 2021)

Figure 3 shows the UAV model used for the aerial data collection. The UAV model used was DJI Inspire 2. The sensor used was a multispectral camera and RGB; Micasense RedEdge-M (Figure 4). This multispectral sensor can be utilized in providing a comprehensive view into crop health such as for species identification, weed detection, crop health mapping, and others application. During one flight session, this sensor could capture five narrow high resolution of spectral band. Aerial data collection was collected on the same day as ground data collection on 30th June 2020 (the day after sowing (DAS) 34). The drone was flying at 60 m altitude at 10:00 am with a spatial resolution of 1.8 cm (multispectral) and 7.95cm (RGB). The weather condition was also good during the data collection.

Figure 3: DJI Inspire 2 (Mohd Firdaus, 2021)

Figure 4: Micasense sensor source from (Micasense, 2020)

3. 2 Image Processing and Analysis

Two types of images were obtained from aerial imagery data collections: the RGB image and Multispectral image. The RGB image was used to make a based plot, while the multispectral image produced the NDVI map. The 8 points from each subplot were plotted in the RGB map. From the NDVI map, the pixel values for each SPAD point in the subplot was taken. All this images processing was done using ArcGIS software. Figure 5 shows the workflows of the image processing.

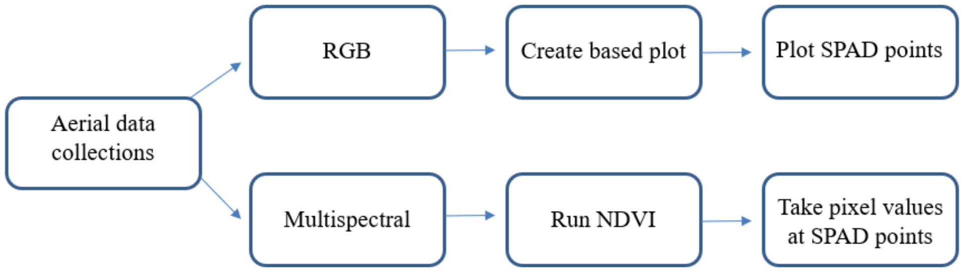

Figure 5: Image processing workflows (Mohd Firdaus, 2021)

A process called image classification is done from the RGB image to develop a weed map. The objective of the classification process is to classify all pixels in a digital image into one of several land covers classes, or "subjects". In this study, supervised image classification is done to classify the paddy, weeds, and soil from the RGB image. Thirty samples were taken and merged using the ArcGIS training sample manager option for every type of class. The image must be well-zoomed and taken using polygon drawing during the sample collection to ensure the correct pixel value was taken. The last step was to run the interactive supervise classification option, and a weed map was developed.

After both ground and aerial data collection had been processed, the next step is to run the correlation between those 2 data. Statistical analysis involves three basic steps: taking out of pixel values according to subplot, calculating the average for each subplot, and running correlation between the NDVI with SPAD data using Statistical Package for the Social Sciences (SPSS) software.

4.0 RESULTS AND DISCUSSIONS

4.1 RGB Map

The plot's boundary was digitized using ArcGIS software from the RGB image. The plot shows the actual representation of the study plot area. The 8 SPAD points from each subplot were also pinpointed on the map. Figure 6 shows the result of the RGB map with the SPAD points in vector format. The NDVI map was generated using the algorithm (Eq. 1) in ArcGIS software from the multispectral image obtained. Figure 7 shows the NDVI map. From this NDVI map, the pixels values of the SPAD point were taken and recorded.

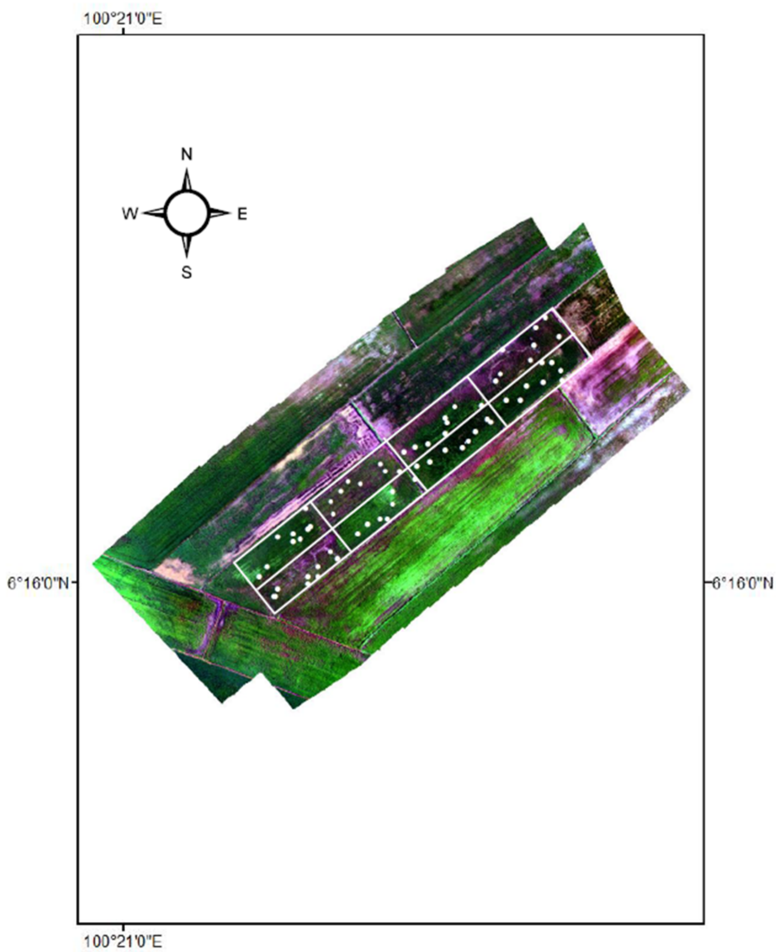

Figure 6: RGB map with the plot boundary and SPAD points in vector format (Mohd Firdaus, 2021)

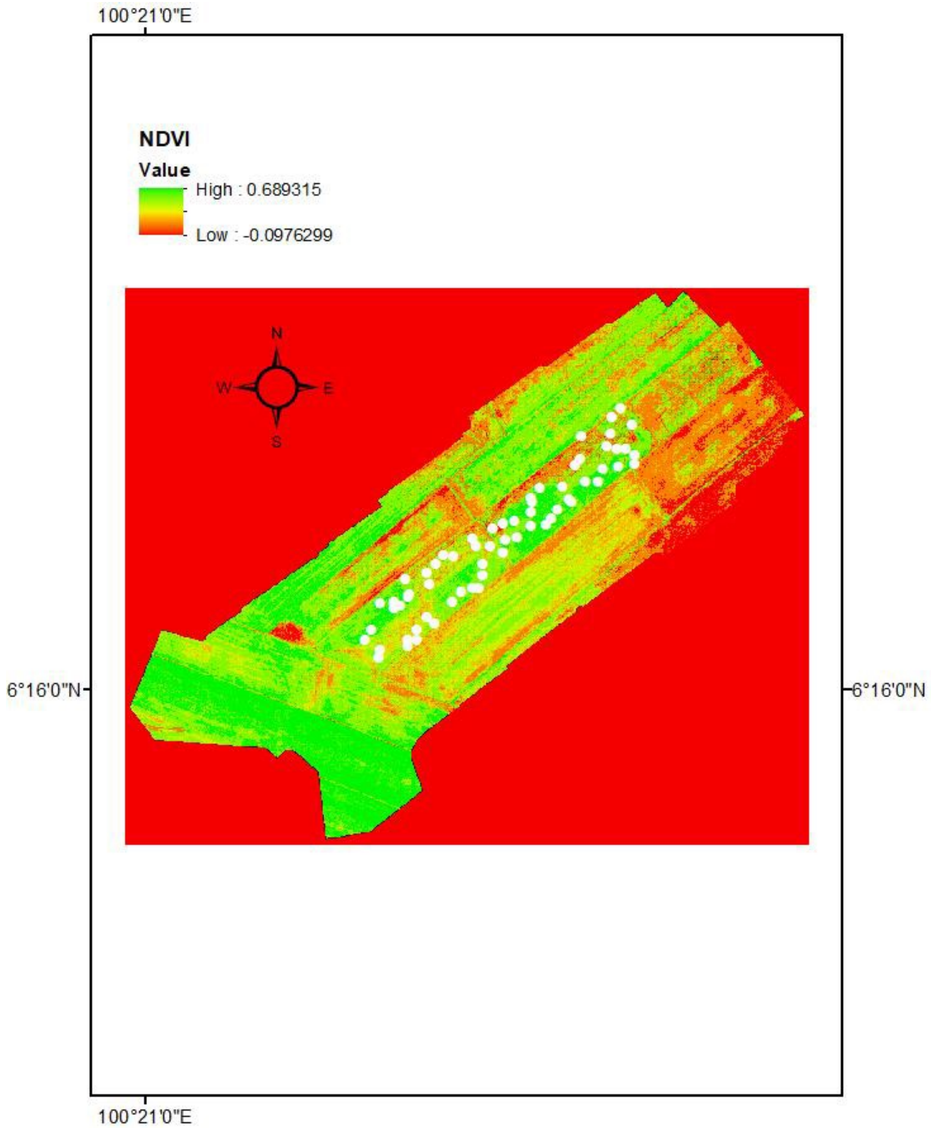

Figure 7: NDVI Map (Mohd Firdaus, 2021)

The green color represents the healthy plant zone, while the yellow represents the less healthy plant zone. The healthy vegetation tends to absorb a visible band and reflect most NIR light. Meanwhile, the unhealthy vegetation reflects less on NIR light and more on the visible band (Tugi et al., 2015). The red color represents low or no vegetation. For subplots that were treated with herbicide and fertilizer, only one plot was very healthy, and the rest were slightly healthy. Most subplots treated with no fertilizer and herbicide were healthy, and only one plot was not healthy. This result was also similar to Reineeke et al. (2017) finding, which able to show the plot vegetations health. Weed map was produced by using ArcGIS software. This map used supervise image classification tools in ArcGIS. Figure 8 shows the result of the weed map.

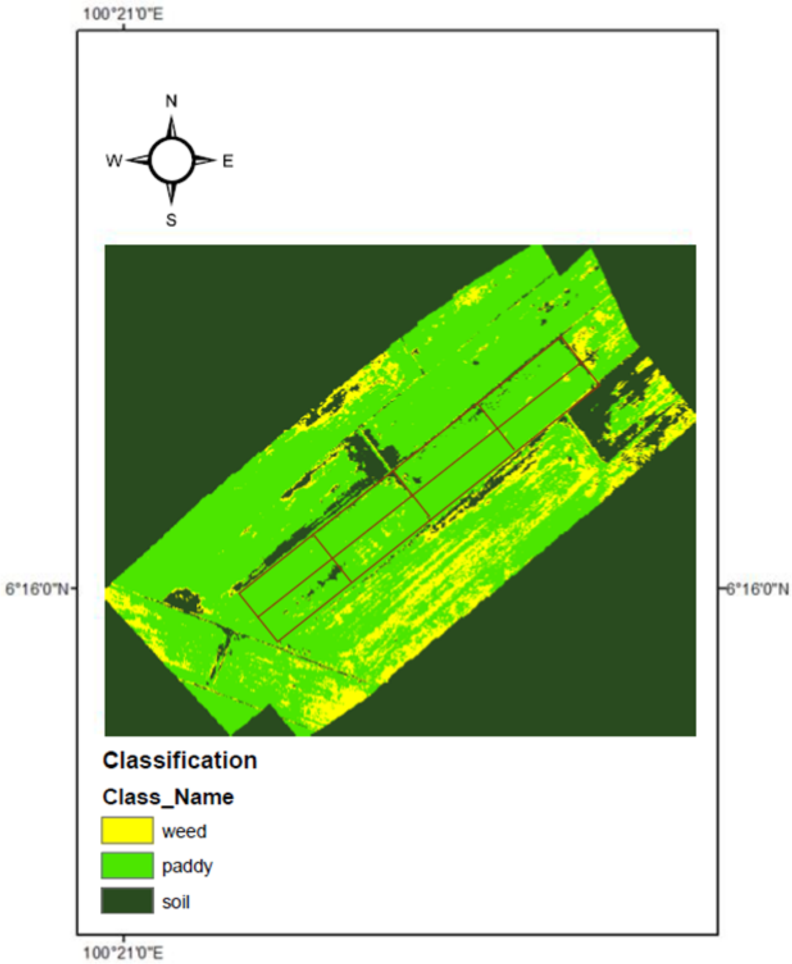

Figure 8: Weed Map (Mohd Firdaus, 2021)

This map can precisely show the location of the weeds and the paddy. The yellow colour indicates the weeds' location, light green for paddy, and dark green for soil. For subplots treated with fertilizer and herbicide, most areas have very little or without weed existence. Only one subplot with this treatment has an immediate amount of weeds. Most rooms have little weeds for subplots with no cure and act as a control. Only one subplot has a large number of weeds.

The farmers can use this weed map as guidance for spraying herbicide. It will help the farmers cut costs for herbicides and save their time. By spraying herbicide at the precise location, it can also help prevent the development of herbicide-resistance weeds. The results obtained in the López-Granados et al. (2016) study was also quite similar for this study. The weeds and the paddy plant were troublesome to be classified and separate based on the spectral reflectance, shape and texture due to both plants nearly having comparable features; hence, extra ground truth data would be required for a further research project to classify the weed precisely (Singha et al., 2016).

4.2 Correlation and Regression Between Spad and NDVI

After the values of SPAD points were taken from the NDVI map, the values were correlated with the ground SPAD points data values. This was done using the SPSS software. SPAD 502 plus Chlorophyll meter was used as the ground truth parameters that measured the nitrogen level. The correlation of the NDVI value from the UAV with SPAD data was weak. It has a positive but has no significant value at the α =0.05 level (2 tail). They may be due to the leaf area of the paddy being small. Hence, the soil has a significant share of reflectance that cause a low correlation of NDVI value (Swain & Zaman, 2012). Other research, such as Islam et al. (2014), achieved a good correlation between the SPAD and NDVI values. Table 2 shows the correlation table, while Figure 9 shows SPAD vs NDVI values. The regression between SPAD and NDVI is shown in Table 3. This study showed that the SPAD values data collection were not well correlated, and it has no significant relationship with the aerial imagery NDVI value.

Table 2: Correlation Table (α =0.05)

		SPAD	SPAD
SPAD	Pearson Correlation	1	0.129
	Sig. (2-tailed)		0.760
	N	8	8
NDVI	Pearson Correlation	1	0.129
	Sig. (2-tailed)	0.760	
	N	8	8

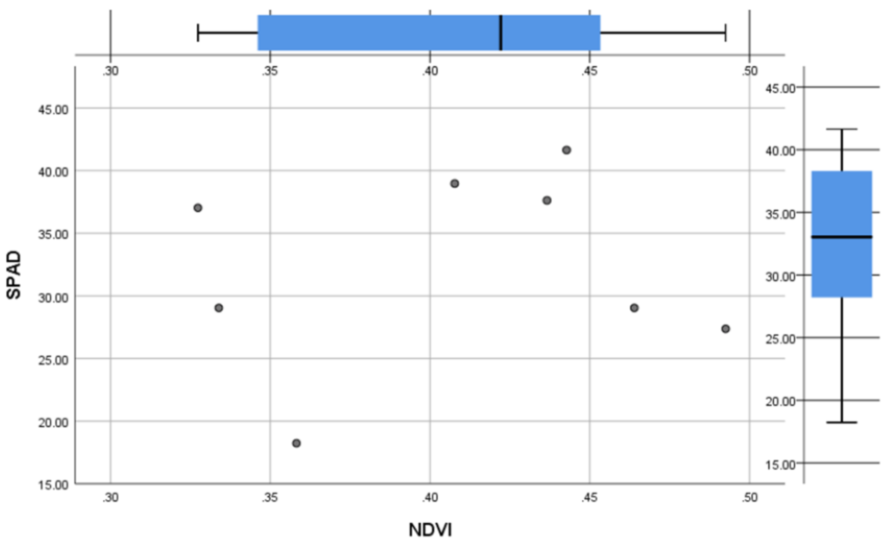

Figure 9: SPAD vs NDVI values (Mohd Firdaus, 2021)

Table 3: Regression Table

Relationship	Regression Equation	R-square
SPAD and NDVI values	y = 18.08x + 25.001	0.0199

5.0 CONCLUSION

Weeds detection utilizing visual ground observation is time-devouring, and it is not a simple assignment to monitor each portion of the paddy field, particularly for more extensive paddy areas. Therefore, the application of aerial imagery such as UAV can be one of the best alternative ways to detect weeds. This study explained the potential use of UAV as one of the modern agriculture tools to see weeds in the field. Although the correlation between the SPAD and the NDVI values was weak, UAV application in the rice field still can detect problems areas in a short time instead of using the conventional method by frequently undergoing time-consuming ground detections.

This study has successfully produced a weed map, which is the main objective, and an NDVI map, which contains a crop health of the area. This weeds map can help farmers detect the weeds problems within the field and create decisions more successfully. It can also help the farmer a lot in terms of money and time and prevent herbicide-resistance weeds. The UAV and the multispectral sensor can easily be obtained from the market, giving a lot of beneficial advantages to the farmers in the future. Farmers in Malaysia should learn and adapt these UAVs technologies to help them manage their farms better.

ACKNOWLEDGEMENT

The authors would like to thank Ministry of Higher Education Malaysia for providing research fund from Long Term Research Grant Food Security Niche Area LRGS/1/2019/ UPM/01/2 Development of climate ready rice for sustaining food security in Malaysia (Vote: 5545000) and also to Lembaga Kemajuan Pertanian Muda (MADA) for allowing us to use their platform by LRGS Climate Ready Rice.

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