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Rice Chlorophyll Content Monitoring using Vegetation Indices from Multispectral Aerial Imagery

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ABSTRACT

Precision agriculture is a concept of agricultural management, based on analyzing, measuring, and reacting to inter and intra-field variability in crops. One of the tools deployed for crop monitoring in precision agriculture is the use of an unmanned aerial vehicle, able to obtain high flexibility with fewer restrictions, and high spatial and spectral resolution in comparison to airborne and spaceborne system. In this paper, the assessment of various vegetation indices were performed for paddy stress monitoring using red edge band from multispectral imagery. The objective of the study was to create rice field maps with the use of aerial imagery and object-based image analysis technique to validate vegetative indices in rice field maps by using soil plant analysis development (SPAD) data. The result showed 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), all of which provided positive linear correlations with SPAD readings. NDRE showed higher correlation compared with other vegetation indices, exhibiting a better measure ment for farmers to make decisions. This paper has demonstrated how aerial imagery can be used to collect an accurate mapping in real time that can be analyzed to monitor

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conditions of crop and chlorophyll content by using SPAD to enable farmers to make informed decisions. Further investigations need to be carried out by validating the real chlorophyll content to improve existing correlations.

Keywords: Multispectral imagery, object-based analysis, red edge band, vegetation index

INTRODUCTION

Rice (*Oryza sativa* L.) is the most important source of livelihood and income of rural population. Currently, the self-sufficiency level (SSL) of rice is 71.5% and SSL needs to be increased up to 80% to feed country's population by 2020. However, rice productivity is too low due to lack of technical efficiency which can be brought to effect for agricultural households (Arellano & Reyes, 2019). Precision farming offer an alternative choice for the farming community for farm productivity improvement. Site-specific crop management is a technique that is designed to integrate various technologies to provide spatially referenced data for better decision making (Norasma et al., 2013; Mukherjee et al., 2019). Crop monitoring and assessment is one of the crucial problems related to yield in agricultural crops. Timely and accurate crop monitoring can provide early treatment to unhealthy crops and can maintain the amount of yield production in agriculture. Traditionally, crop assessment had relied on ground-based field survey and visual observation to measure plant status by collecting a small sample size (Sim & Gamon, 2012). Common techniques, including manual inspection and perimeter scouting, are inefficient methods for data collection and validation process (Valente et al., 2011). For instance, ground assessment is to ascertain crop status which involves measurement of a plant by using its leaf. However, the crop assessment for an agricultural field requires an up-scaled information beyond the canopy level. Moreover, the collection of ground samplings in the field was slow and costly. According to Zhang et al. (2015), implementing this type of collection for crop assessment in the field would be tedious. Regular remote sensing technique by placing a sensor on a stronghold over crop fields, as well as weather constraints, was a limitation for data collection (Nguy-Robertson et al., 2012). Likewise, using a satellite and piloted aircraft demonstrated a constraint with temporal and spatial resolution for agricultural assessment (Maes & Steppe, 2019).

Therefore, applying a quick, efficient, and accurate method for crop monitoring and assessment is crucial in increasing productivity and efficiency in the field. Remote sensing technology is a reliable tool to assess crop health and status, such as chlorophyll collection (Haboudane et al., 2002), leaf area indicator (Wang et al., 2019; Liu et al., 2017), and biomass (Fu et al., 2014), which can effectively be correlated with remote sensing information. In precision agriculture, crop condition can be monitored using remote sensing based on the crop parameter. In general, remote sensing is a means of obtaining and interpreting information of an object from a distance, an area phenomenon by acquiring the data using sensors or devices without physical touch (Johnson et al., 2003). Remote sensing typically uses sensors to reach aerial, satellite, and orbital observations on the surfaces and the targeted objects (Zulfa & Norizah, 2018; Ren et al., 2018). Satellite images have been used as the primary source of information for analyzing crop health in precision farming (Auernhammer, 2001). However, satellite and aerial remote sensing have their own limitations. In contrast, UAV technology can identify the details of an area because of higher spatial resolution and this type of imagery provides new solutions for crop management and monitoring in agricultural fields (Abdullah et al., 2019). High-resolution imagery and real-time satellite imagery are expensive. The limitation of satellite remote sensing is cloud cover, which contributes to low pixels resolution in unclear imagery (Verger et al., 2014).

The Development and UAV-based Application for Crop Management and Monitoring

The advanced development of UAV has provided another alternative for crop management and monitoring in large areas (Li et al., 2019). The application of UAV technology in crop assessment has functions in various crops for monitoring health status of crops. This would ease farmers in managing their farms and provide more accurate data regarding their crop conditions in the field. UAVs equipped with visible band and multispectral scanning sensors can provide enough information for analysing crop growth, health status, maturity, and morphology. Imagery from UAV, using different sensors like RGB (Red Green Blue), multispectral, hyperspectral, and thermal camera have been used to estimate leaf area indicator (LAI) (Wang et al., 2019), biomass (Bendig et al., 2015), carotenoid (Zarco-Tejada et al., 2012), and temperature (Tokekar et al., 2013). Shafri et al. (2006) demonstrated the usefulness of a multispectral camera mounted UAV to examine the emergence of wheat during early season from UAV imagery applying vegetation index. Louis et al. (2005) had proven that the use of UAV technology with a multispectral sensor provided a higher spatial resolution for wheat monitoring in the emergence stage. This was supported by Sullivan et al. (2007) who investigated hyperspectral data acquired from UAV platform to perform quantitative analysis for rootstock performance in walnut trees.

The developmental progress of UAV has improved from slow-flying UAV (Berni et al., 2009) to fixed wing and rotary-UAV, where the advantage is that flight characteristics due to their natural gliding capabilities with no power. In addition, Norasma et al. (2018) experimented on crop status using UAV with optical sensors and had successfully identified stressed area using water flow analysis at the early season of rice growth. Table 1 shows the types of UAV application for different purposes of crop assessment.

Table 1
Different types of UAV application in crop assessment

UAV type	Objective	Camera	Crop	Reference
RCTAS/APV-3 Unmanned aircraft	Usefulness of UAV's for precision agriculture	Hyper-spectral	Grapevine	Kira et al. (2015)
Unmanned helicopter	Tree canopy conductance, crop water stress index	Airborne Hyper-spectral Scanner	Corn Olive Peach and olive	Berni et al. (2009)
Unmanned helicopter	Development small UAV for agriculture surveillance Assess water stress	Thermal	Turf grass	Xue & Su (2017)
Fixed- wing	Water stress	Narrow-band multi-spectral Thermal	Grapevine	Zarco-Tejada et al. (2012)
Multirotor UAV	Weed detection	MCA 6 Multi-spectral	Sorghum	Norasma (2016)

Berni et al. (2009) found that thermal sensing could be used for irrigation management and the sensor can read characterization of water stress in the orchards. However, the sensor is expensive and needs an expert pilot to fly the UAV to collect the data. This is similar to Kira et al. (2015) that also used hyperspectral sensor and found that VI gave the highest results compared to NN and PLS model. Zarco-Tejada et al. (2012) experimented the effectiveness of narrow-band indices such as chlorophyll indices like fluorescence indices (FLD2) and xanthophyll, showed promising result than NDVI for water stress detection. The result indicated the spectral index that comprised the wavelength near red edge region such as 747nm, 762nm and 780nm were the best indicators in monitoring crop status. Therefore, the use of VI is important to improve the sensitivity of the greenness of the plants (Xue & Su, 2017) and consistently with Norasma (2016) that also used VI and OBIA to detect weed in sorghum crop. Norasma (2016) and Xue and Su (2017) suggested to develop new VIs for the broadening of the research areas. In addition, Norasma (2016) found that the overall accuracy for weed detection using OBIA was more than 80%. These results are considered high and moderate for the effectiveness in discrimination respectively (Norasma, 2016). Therefore, the OBIA technique was used and calculated the VIs for accurate rice mapping using multispectral sensor due the cost effectiveness.

Chlorophylls is a major and integral part for the reaction of photosynthesis, and this is suitable as remote sensing could assess plant physiological development (Yongjun & Jingjing, 2016). The quantity of chlorophyll per unit leaf area in a plant is a key status of the entire plant's health. Healthy plants with the capability of displaying growth rates until optimal extent is estimated to have higher amounts of chlorophyll than unhealthy plants. Thus, the identification and detection of chlorophyll content in a leaf can be used to detect and study plant stress, based on its nutritional form, contributing a crucial effect on crop status and conditions, the level of severity, and the amount of nutrients, especially in precision agriculture practices (Zarco-Tejada et al., 2013). Vegetation indices and red edge-based indices are the most general techniques that can be used in plant stress detection. Vegetation indices are widely used for the estimation of crop status based on the amount of chlorophyll content by using visible and near-infrared (NIR) regions of the electromagnetic spectrum. Chlorophylls have strong absorption peaks in the red region and high reflectance peaks in the near-infrared region (Shamshiri et al., 2017). Maximal absorbance in the red region occurs between 660 nm and 680 nm. This is because absorption range of 660 – 680 nm tends to be saturated at low chlorophyll quantities and reflect in the near-infrared region, thus reducing the sensitivity of the spectral indices based on this wavelength, except for high chlorophyll content (Singh et al., 2017)

In recent years, numerous spectral indices from UAV have been proven to calculate plant disease detection and crop monitoring (Garcia-Ruiz et al., 2013; Hunt et al., 2018; Yoder & Pettigrew-Crosby, 1995). Multispectral (MS) and hyperspectral sensors mounted on UAVs have been extensively used to assess plant health and conditions for several vegetation indices, which involved integrated R515/ R570 (band ratioing) and TCARI/ OSAVI narrow-band indices for leaf chlorophyll estimation with a hyperspectral camera mounted on UAV (Liang et al., 2015; Wang et al., 2019). Hunt et al. (2003) proved that colour-infrared film used with a low-cost automatic camera produced a Normalized Difference Vegetation Index (NDVI) map that can be used in crop monitoring. Table 2 shows the sensor of different remote sensing platforms in crop disease inspection.

Ranganath et al. (2004) proved near-infrared region had shown considerable reduction in reflectance in differentiating diseased rubber from healthy rubber using multi-date satellite data of IRS-1C. This is similar to the work of Shaw and Kelly (2005), using multispectral satellite imagery in classifying soybean anomalies from infestation. This is attributed to differences in colouration of soybean plants with iron chlorosis and lack of full canopy coverage of stunted soybean. However, previous studies were not sufficient for crop

Table 2
Example of disease detection of crop by various remote sensing methods

Crop types	Sensor	References
Rubber plantation	Indian remote sensing satellite (IRS-IC)	Ranganath et al. (2004)
Soybean	Multispectral sensor	Shaw & Kelly (2005)
Paddy	Hyperspectral radiometer (ASD fieldspec pro FR)	Ren et al. (2008)
Oil palm	Hyperspectral sensor, APOGEE spectroradiometer	Shafri & Anuar (2008)
Wheat aphids	Handheld cropscan radiometer	Yang et al. (2009)
Oil palm	AISA airborne hyperspectral sensor	Shafri et al. (2011)
Grapevine	Narrow-band multispectral thermal UAV	Zarco-Tejada et al. (2013)
Onion Cultures	Multispec 4C protype (Ebee) UAV	Nebiker et al. (2016)
Walnut trees	Hyperspectral sensor	Singh et al. (2017)

monitoring due to lack of narrower spectral bands such as hyperspectral data. Therefore, Ren et al. (2008) and Shafri et al. (2011) proved that hyperspectral crop reflectance data could be used in monitoring crop growth and development using VI and spectral signatures. Nebiker et al. (2016) showed that NDRE index showed an average correlation and had better performance than NDVI in detecting disease in onion using light-weight multispectral UAV sensor. Singh et al. (2017) had further proven that red-edge position index, which fell in the wavelength of 680-780 nm was a better preference in monitoring rootstock growth in walnut trees using UAV-based remote sensing.

Singh et al. (2017) had shown how a multispectral sensor could be used to examine the emergence and growth stages of wheat from UAV technology using a sequence of vegetation indices. Andre et al. (2013), had reported a stronger relationship between vegetation and leaf area index (LAI). Moreover, vegetation indices made up of red edge band (720 nm) and near-infrared band (800 nm) were found to be more effective in estimating yield and amount of chlorophyll present at higher state. In this study, multispectral images in the early season of rice growth were obtained using UAV technology, and vegetation indices were correlated to SPAD chlorophyll meter readings to assess the potential of several vegetation indices for examining amount of chlorophyll concentration present in rice. The objective of this study was to examine four vegetation indices using aerial images and object image analysis (OBIA), and to correlate with the vegetation indices in paddy field maps using the chlorophyll data from SPAD meters.

MATERIAL AND METHODS

The research was carried out at Ladang Merdeka, Ketereh, Kelantan, located in the east coast of Peninsular Malaysia (Figure 1). The whole coverage of the study area is twenty acres. The coordinates of the study location are 6.076184°, 102.184315°. The plots were thoroughly prepared and levelled using a leveler machine. Rice variety called PadiU putra, which is resistant to leaf blight disease (S1) was used in this present study.

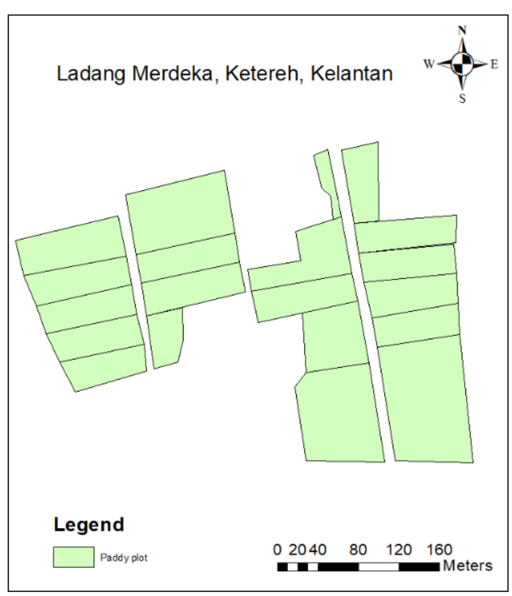


Figure 1. The experimental plot in Ladang Merdeka

This study was developed and managed by UPM researchers for a single season from January 2018 until May 2018. The cultivated medium of PadiU Putra (S1) was planted on 30th January 2018. Figure 2

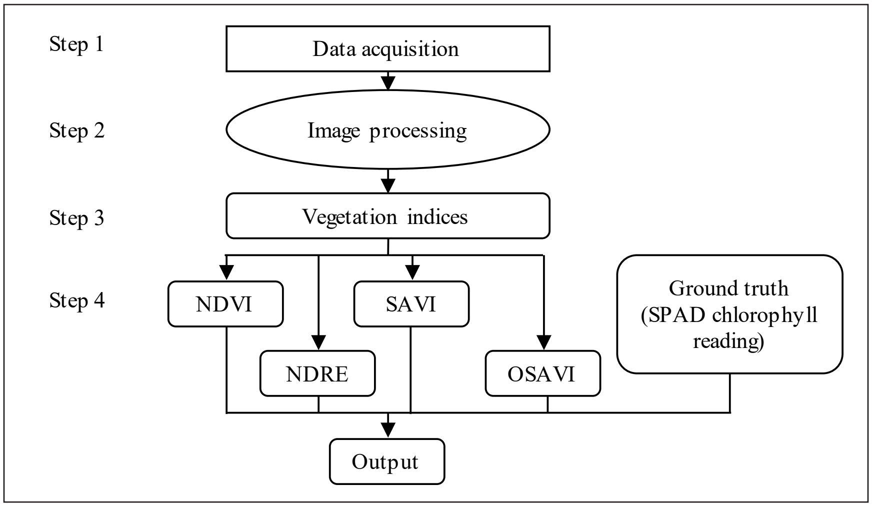


Figure 2. The methods steps in this study

shows the flow chart of this research, indicating the performance of difference vegetation indices at early season of rice growth.

Data Acquisition

Step 1: Collection of Ground Samples. The ground chlorophyll diagnostic tool used in this study was SPAD 502 chlorophyll meter (Konica Minolta Sensing, Inc., Osaka, Japan). Five samples from eight points within 1 m radius were scanned using SPAD chlorophyll meter and these samples were then recorded and averaged to obtain the accurate result.

Image Acquisition

For image collection, a multirotor UAV and multispectral camera were used. The flight plan was designed prior to data acquisition by using Mission Planner software (http://ardupilot.org/planner/index.html). Mission planner is a ground control station for ArduPilot created by Oborne (2019), providing setup and flying support, as well as reviewing recorder flights. The multispectral sensor mounted on the drone was Parrot Sequoia, which was manufactured in Paris, France. It was able to capture 4 types of wavebands, and they were green band, red band, red edge, and NIR (Markengold PR, 2016). The data collection was conducted at daytime under less cloudy and windy conditions, between 08:30 a.m. until 12:00 p.m. (+8 GMT) on 10th of February 2018 on the 11th Day After Planting (DAP). Agisoft Photoscan software (Agisoft LLC, St. Petersburg, Russia) was used to build and arrange the imagery mosaic using Structure from Motion (SfM) algorithms. Table 3 shows specification of the multispectral camera used.

Table 3
Basic parameters for multispectral camera on UAV

Sensor	Spectral bands (nm)	Resolution (pixels)	Weight (g)
Parrot Sequoia	530, 640, 730, 770	1280 × 960	107g

Step 2: Image Processing. Pre-processing of raw images involved downloading them from the SD memory card to the computer and then further processing them in Agisoft Photoscan Professional software (Agisoft LLC, St. Petersburg, Russia) to produce orthophoto map. Then, the orthophoto map was geo-rectified using the control points at the field. The geo-rectified process use ArcMap software to validate the orthophoto map. Subsequently, the orthophoto map was analysed using eCognition software. eCognition software (Definiens AG, Munich, Germany) is a development environment for object-based image analysis (Andre et al., 2013).

Data Analysis

Step 3: Vegetation Analysis for Different Vegetation Indices. Four types of vegetation indices were used for monitoring the crop condition in the rice field. Normalized Difference Vegetation Index (NDVI), Normalized Difference Red-Edge Index (NDRE), Soil Adjusted Vegetation Index (SAVI), and Optimized Soil Adjusted Vegetation Index (OSAVI) indices were chosen for the multispectral images such as green band, red band, red edge, and NIR images. Vegetative maps for different vegetation indices were produced for NDVI, NDRE, SAVI, and OSAVI. Table 4 provides information on vegetation indices including red-edge indices were applied in this this UAV-imagery. This processing step was performed using eCognition software.

Table 4
Vegetation indices and red edge algorithms were applied in this UAV-imagery

Vegetative Index	Algorithm formula	Author
NDVI	(NIR-RED) / (NIR+RED)	Rouse et al. (1974)
NDRE	(NIR-RED EDGE) / (NIR+RED EDGE)	Fitzgerald et al. (2006)
SAVI	(1+L) * (NIR-RED) / (NIR+RED+L)	Huete (1988)
OSAVI	(1+l) * (NIR-RED) / (NIR+RED+L) Where L= 0.16	Rondeaux et al. (1996)

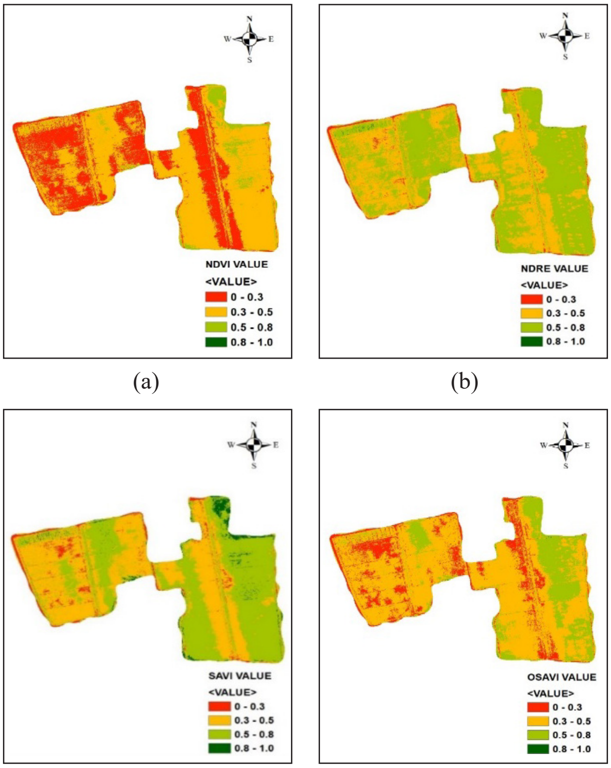
Step 4: Statistical Analysis between Vegetative Indices (NDVI/ NDRE/ SAVI/ OSAVI) with SPAD Readings. Statistical analysis between NDVI/ NDRE/ SAVI/ and OSAVI values obtained from multispectral imagery were correlated with ground samples (SPAD chlorophyll values). Vegetative indices were correlated and validated to compare two different vegetative indices, such as NDVI/ NDRE/ SAVI/ OSAVI with SPAD units using

Pearson correlation analysis. Besides, the root mean squared error (RMSE) for each iteration was computed and averaged to determine coefficient of variation (CV). The lower the value of the CV, the more precise the estimate is. This analysis was run by Minitab® 17 Statistical Software.

RESULT AND DISCUSSION

Vegetation Analysis

Figure 3 shows the VI map at early season of rice growth. The range of values for the NDVI/ NDRE/ SAVI/ OSAVI is -1 to 1 where -1.0 represents very low level of vegetation greenness and 1.0 represents very high level of vegetation greenness. Vegetation indices, such as NDVI, NDRE, SAVI, and OSAVI, usually have values closer to 0, indicating lesser canopy density, whereas values closer to 1 indicate more canopy density for crops (Xiang & Tian, 2011). Since four different VI were used, the outcomes were different because each indices is for different purpose. This project shows that the results were as expected based on the literature. In the early phase of rice growth, the canopy area of the rice crop was small, and most of the reflectance were affected by soil and water factors, which could influence the result on vegetation indices (Garcia-Ruiz et al., 2013). Most rice crop in the early season fall in the yellow zone, with NDVI values ranging from 0.3 to 0.5 because soil background effects during the growth stage of the rice plants. This is consistently found where NDVI is sensitive to the effects of soil brightness, soil color, atmosphere, cloud and cloud shadow, and leaf canopy shadow (Xue & Su, 2017). Whereas OSAVI and NDRE showed promising indices that were able to capture some smaller plants inside the paddy field, due to elimination of soil background



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

Figure 3. Vegetation indices map generated during early season (on the 11`th Day After Planting (DAP) of rice growth: (a) NDVI map; (b) NDRE map; (c) SAVI map; and (d) OSAVI map

effects and larger the effect of photosynthesis even though it fell at the early season of growth (Li et al., 2019; Rouse et al., 1974).

Relationship Between Vegetation Indices and SPAD Chlorophyll Readings

There was a positive linear correlation between NDVI and SPAD readings. NDVI shows higher correlation with SPAD readings (R = 0.957; RMSE= 0.74) (Figure 4). This relationship is consistent with those of other studies which also reported a positive and linear relationship between vegetation index (NDVI) and ground data such as SPAD chlorophyll readings and nutrient content. Zhou et al. (2017) suggested that vegetation index, such as Normalized Difference Vegetation Index (NDVI), could be used to identify rice crops' characteristics. Likewise, there was a positive linear correlation between NDRE and SPAD readings. NDRE showed a high correlation with SPAD readings (R = 0.974; RMSE= 0.576) (Figure 4). Additionally, the result supports the theory that green and red edge region are highly responsive to a broad range of chlorophyll levels in red region only (Carter & Knapp, 2001). Figure 3 shows NDRE values, which indicate the status of chlorophyll content in the early stage of the rice plants' growth between red edge conversions. The normalized difference of the red edge index (NDRE) is made of red edge band (700-740 nm). A conversion area of rapid shift in leaf reflectance, caused by higher chlorophyll absorption in the red region and leaf scattering in the near-infrared spectrum, has been found to be related to plant health (Niinemets & Tenhunen, 1997). NDRE values can show the chlorophyll content in the early phase of rice growth, as the value range is between 0.5 and 0.8 as shown in Figure 3(b). This was because soil and water background factors were not considered. Furthermore, this is related to the distinct emission in the red edge region, which penetrates deeply into the crop canopy and plant leaves compared to visible light (especially blue and red radiation) because of the lower chlorophyll absorption in this region. This is useful in monitoring crop N status based on the amount of chlorophyll content but does not perform well in examining crop growth stage when there is less fluctuation in plant N concentration (Li et al., 2012). Particularly, the sensitivity of absorbance could be linked to plant chlorophyll content that is higher than that of the red edge region (Niinemets & Tenhunen, 1997). The red edge band is a spectral reflectance feature whereby the characterization of red portion showing in red portion of the visible spectrum, due to the absorption by chlorophyll. In contrast, high reflectance in the NIR due to light scattering from refraction along interfaces between leaf cells and air spaces inside the leaf (Zhang et al., 2015). Also, Soil-adjusted vegetation index (SAVI) showed higher correlation with SPAD readings (R = 0.964; RMSE= 0.676) (Figure 4). Soil-adjusted vegetation index (SAVI) can be another adjusted index for NDVI, as NDVI has its own limitation when connections are being made across various soil types that may reflect different amounts of light in the red and near infrared wavelengths (Li et al., 2014).

Soil-adjusted vegetation index (SAVI) was developed as an improvement of the NDVI to reduce the influence of soil brightness when vegetative area is sparsely distributed (Huete, 1988). In addition, soil-adjusted vegetation index SAVI (Figure 4) reduces soil background noise effects. This was further supported by Ren et al. (2018), showing that the negative soil adjustment factor was the factor of the increase of the slope of vegetation contour and the positive intersected points between vegetation isolines and soil. For example, it happened in the first quadrant of the NIR-red plane. Optimized soil adjusted vegetation index (OSAVI) indicates high correlation with SPAD readings (R = 0.966; RMSE= 0.664) (Figure 4). In this analysis, the performance of OSAVI was similar to SAVI, as the standardized vegetation indices, to further fit the purpose of this study and to reduce the possibility of soil background effect; this was in agreement with other vegetation studies (Rondeaux et al., 1996). The validation was done using SPAD value, where it showed higher correlation and validated method were supported by the work of Basca et al. (2019). Table 5 shows the summary of the relationship between ground data (chlorophyll readings) and vegetation indices as well as RMSE. Spatial trend of SPAD chlorophyll map is shown in Figure 5. Bato (2018) stated that GIS-based suitability mapping was momentous to enable the creation of a spatially accurate suitability map like spatial distribution of nitrogen in this study and contributing of great moment in decision making process for farmers.

Table 5
Relationship between NDVI, NDRE, SAVI and OSAVI with chlorophyll readings (SPAD) using Pearson correlation and RMSE

	SPAD	
Vegetation index	R	RMSE
NDVI	0.957	0.74
NDRE	0.974	0.576
SAVI	0.964	0.676
OSAVI	0.966	0.664

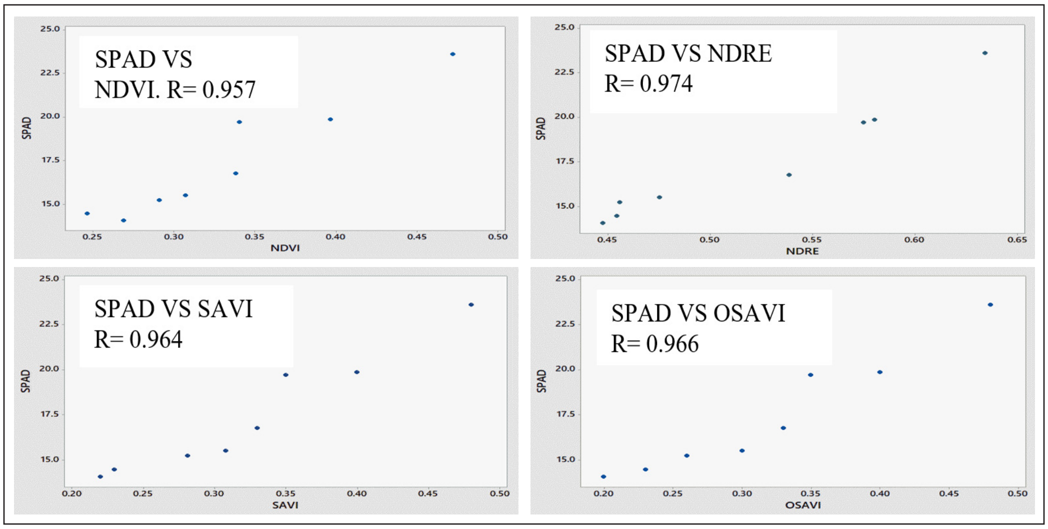


Figure 4. Relationship between SPAD chlorophyll readings, NDVI, NDRE, SAVI and OSAVI using Pearson correlation analysis in scatter plot

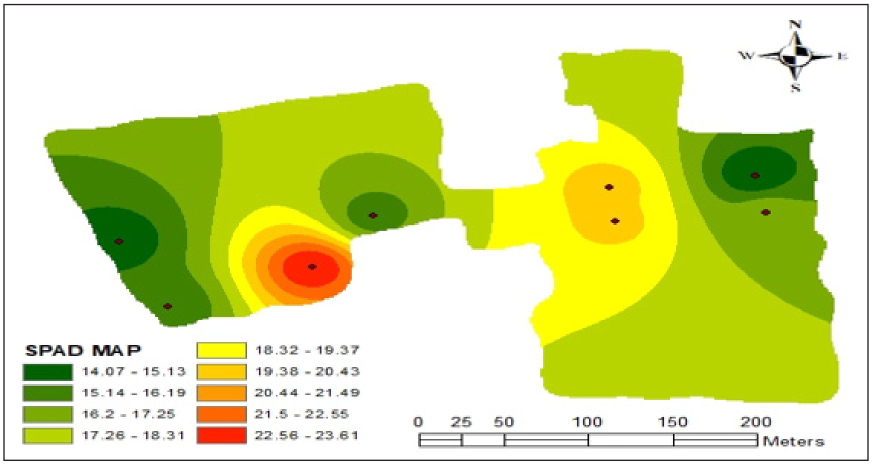


Figure 5. SPAD chlorophyll map for Ladang Merdeka

CONCLUSION

Vegetation indices, known as NDVI, NDRE, SAVI, and OSAVI, were tested in this study to investigate their ability in the estimation of the amount of chlorophyll by the multispectral sensors, which comprised only four spectral bands (530nm, 640nm, 730nm, 770nm). The findings showed the strongest correlation is NDRE (R=0.974; RMSE= 0.576), followed by OSAVI (R=0.966; RMSE= 0.664) and SAVI (R=0.964; RMSE= 0.676). The lowest correlation is NDVI (R= 0.957; RMSE= 0.74). NDRE was among the best indicators in estimating the status of chlorophyll content in paddy, while providing an overall map for farmers to calibrate their agricultural input, such as increasing the input to stressed areas while reducing the input to the healthy areas, where necessary. Future research needs to focus on sensors with lesser gap of spectral bands (hyperspectral). Namely in the red edge region, specifically the blue shift of the red edge, which has potential for crop monitoring in agriculture. By having a vegetation index map, farmers can easily track the crop growth and the condition of the paddy in real-time (Figure 3). However, more points should be added for SPAD data collection in the future to acquire good variable maps and accurate spatial distribution. Studies need to be done for further assessment and validation to test the accuracy and efficiency of this technology. With that, the goal of applying the concept of precision agriculture can be achieved in the operation. By that, it helps farmers in their management and crop condition monitoring. It fulfills the gap of crop monitoring in agricultural practices and sustainable production in real time.

FUTURE DIRECTION

The future potential of UAV technology can serve as a powerful tool to collect accurate and high-resolution images for spatial data. Meanwhile, image processing can be adopted with more advanced computer vision and machine learning algorithms. Several machine learning algorithms can be further applied on UAV based multispectral imaging using programming application such as python and other related web-based programmed cloud processing should be applied in the near future due to the size of the data. The analysis output then can be transferred to the automation and robotics in real-time for decision-making process and quick responses.

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