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Rubber-Tree Leaf Diseases Mapping Using Close Range Remote Sensing Images

Abd Wahid Rasib[1], Nurmi-Rohayu Abd Hamid[2*], Muhammad Latifi Mohd Yaacob[1], Zarawi Abd Ghani[2], Nurul Hawani Idris[1], L M S Alvin[1], Muhammad Imzan Hassan[1], Khairulnizam M Idris[1], Rozilawati Dollah[3], Anuar Mohd Salleh[4], Mustaffa Anjang Ahmad[4]

[1]Faculty of Built Environment and Surveying,
Universiti Teknologi Malaysia, 81310 Johor Bahru, Johor, MALAYSIA

[2]Malaysian Rubber Board, RRIM Research Station Sg. Buloh, 47000 Sg. Buloh, Selangor, MALAYSIA

[3]School of Computing, Faculty of Engineering,
Universiti Teknologi Malaysia, 81310 Johor Bahru, Johor, MALAYSIA

[4]Center of Geomatic and Disaster Prevention, Faculty of Civil Engineering and Built Environment,
Universiti Tun Hussein Onn Malaysia, 86400 Parit Raja, Johor, MALAYSIA

*Corresponding Author

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Abstract: Currently, close-range remote sensing method using drone-based platform which payload compact sensor has been used for monitoring and mapping in the agriculture sector at large area. Thus, this study is deployed drone with a compact sensor to identify the rubber tree leaf diseases based on two groups of a spectral wavelength which are visible (RGB: 0.4 µm – 0.7 µm) and near infrared (NIR: 0.7µm – 2.0 µm), respectively. Spectral obtained from drone-based platform will be validated using ground observation handheld spectroradiometer. Eight types of rubber tree clones leaf at three different conditions (healthy, unhealthy and severe) were randomly selected within the 9.4-hectare experimental rubber plot, Rubber Research Institute of Malaysia (RRIM), Kota Tinggi, Johor whereby consist RRIM 2000 series, RRIM 3000 series, and PB series, respectively. Based on the result, quantitative analysis shows that the f-value is smaller than Critical-one tail for healthy, unhealthy while for severe the f-value is larger than Critical-one tail. The f-value is 2.887 < 4.283 (healthy), 0.002 < 0.264 (unhealthy) and 1.008 > 0.0526, respectively. Thus, this can be concluded that spectral and estimate is equal at the 0.05 significant levels. While qualitative analysis shows that each rubber clone tree diseases can be distinguished at the near infrared band for healthy, unhealthy, and severe, respectively.

Keywords: Rubber-tree leaf, diseases mapping, close range remote sensing

1. Introduction

Natural rubber (NR) and rubber wood are the two major products derived from the rubber tree (Hevea brasiliensis). The NR is widely used from household goods to industrial products such as tires and latex gloves. Generally, rubber

*Corresponding author: nurmi@lgm.gov.my

cultivated area in Malaysia was planted by smallholders which are about 92% of total rubber output and the remaining by estates. However, the rubber produced by the smallholders is still low as many of them did not adopt the latest technology, particularly in rubber harvesting due to financial constraint and less confidence of the new technologies [1]. The conventional ground-based survey method not only requires high labor cost, but also produces low efficiency and impractical for a large area. In contrast, the application of remote sensing technology is possible to provide spatial distribution information of the large area.

Remote sensing allows observation of crop fields repetitively and is increasingly explored as an effective approach for real-time crop monitoring and crop yield estimation at both local and regional scales [2], [3]. It is known that disease infection can be detected successfully by remote sensing for several crops such as yellow rust in winter wheat [4], [18], citrus green disease [5], [19], tobacco [6], [20], rice [7], [21], vegetable crops [8], [22] and oil palm [9], [10], [23]. Similarly, the attempt of detection diseases in rubber plantation using remote sensing have been carried out. In India, detection of disease outbreak can be monitored using satellite data for Corynespora and Gloeosporium fungi during the crisis in order to take up suitable treatment measures [11]. Furthermore, Kamaruzaman [12], shows that by using remote sensing technology, rubberwood volume can be quantified as well, while Azizan et al. [24], has publish a review on the remote sensing applications in rubber plantations that gives insight into how remote sensing can be used to improve the efficiency and long-term viability of rubber plantation services.

Currently, the application of remote sensing technologies for crop management has been widely used to increase the efficiency of agriculture input, monitoring crop growth, and health, and also yield estimation. The latest technology for mapping in remote sensing is drone-based platform or so called as unmanned aerial vehicle (UAV) which category under close-range remote sensing. UAV can be defined as an aerial vehicle that capable of sustained flight without a human operator on board. The implementation of UAV method in agriculture production is more productive compared to other type remote sensing technology. UAV method reduces the days in field survey and manpower as compared to air-borne [13]. Furthermore, UAV technology provide a very high resolution which is 2 cm to 10 cm compared to the satellite platform with a resolution between 0.5 m to 10 m. In addition, UAV offers better spatial and temporal resolution, a high-speed and low cost, and easier solution in agriculture production [14]. Besides that, the use of UAV in agriculture can utilize the process of collecting additional data on water access, changing climate, wind, soil quality, the presence of weeds and insects, varying growing seasons, and more [25]. Therefore, this study will demonstrate that UAV can be used as a platform to analyses rubber cultivated areas especially in identifying the physical condition of the rubber tree.

2. Methodology

The research methodology used in this study is consists of four stages. The first stage is research design and planning which essential to be conducted, in this stage all information or past research regarding this topic is collected to discover the issues and problem that arise regarding this topic. The second stage is data acquisition that will discuss the collection of fieldwork data using unmanned aerial vehicle (UAV) and a spectroradiometer. The third stage is data pre-processing and data processing. In pre-processing, the produce of UAV imagery will run into the process of layer stitching, layer stacking, and geometric correction. The spectroradiometer data will undergo the process of spectral filtering. In processing, several processes occurred which is producing vegetation indices and generating disease modeling using the digital number. The last stage is the result and analysis, the end product of this research is rubber tree disease map and analysis.

2.1 Research Design and Planning

There are three main components in the research design which is (i) discover the issues and problems (ii) discover knowledge about the research by reviewing previous research based on literature review, and (iii) identify data sources and designed a research methodology based on the purpose of the research. Fig. 1 shows the framework of this research an overall view.

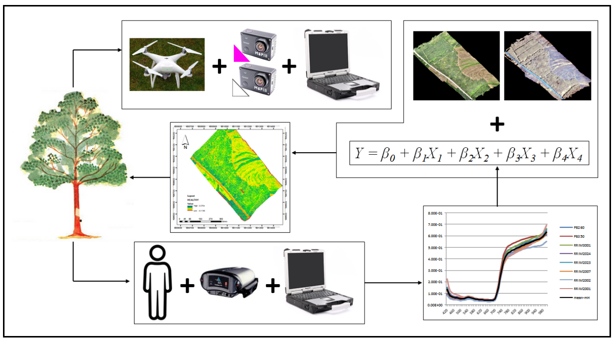


Fig. 1 - Research design and planning

2.2 Data Acquisition

The main components of data acquisition are the fieldwork and site information. The field work will cover the GPS observation, UAV observation, and spectroradiometer observation. The observation was conducted the same day in order to ensure the leaves are still in good form and fresh. Subsequently, the site information will be provided by MRB (Malaysia Rubber Board) with regard to the research area such as size, soil type, rubber leaf information and also a variety of rubber clones planted.

2.2.1 Field Data Acquisition

For data acquisition in the field, GPS observation is required to be carried out first followed by UAV and spectroradiometer data collection. Both UAV and spectroradiometer data collections would be done simultaneously. GPS observation was carried out using Topcon GR-5 for establishing ground control point with coordinate reference. The control points were used to execute correction in mosaicking and layer stacking process. The technique used for GPS observation is static observation. A Malaysian Real Time Kinematic Network (MyRTKnet) observation was carried out to establish ground control point.

UAV is used to collect aerial images in order to compare the quality of data collector of spectral reflectance using a compact camera and spectroradiometer. Then, the digital number derived from both data collector was compared and a model of disease is generated. In order to fly the UAV, a flight planning is necessary. Few parameters need to be considered in UAV flight planning such as camera orientation, altitude, angle and survey speed. In this study, RGB and NIR images were derived from MAPIR camera.

To observe the spectral reflectance, a FieldSpec Handheld Spectroradiometer was used in this study. Mature leaves were selected based on rubber clones and their physical condition of healthy, unhealthy, and severe infection of Oidium leaf disease. The spectral reflectance observation was carried out in a control environment room. An artificial light source and a tripod were used to ensure the consistency of the spectral reflectance obtained from spectroradiometer.

2.2.2 Site Data Acquisition

In this part, leaf disease infection and rubber clones' information were collected. This information is provided by Malaysian Rubber Board (MRB). MRB provides the information of the severity of Oidium leaf disease infection on rubber leaf based on human observation through eye view and details of rubber clones planted in the research area. Fig. 2 shows the leaf sample for healthy, unhealthy, and severely infected on rubber leaf respectively.

(a) Healthy leaf (b) Unhealthy leaf (c) Severe leaf

Fig. 2 - Physical reference of rubber leaf for (a) healthy leaf; (b) unhealthy leaf and; (c) severe leaf

Eight (8) rubber clones were used that are clone PB 260, PB 350, RRIM 2001, RRIM 2002, RRIM 2007, RRIM 2023, RRIM 2024 and RRIM 3001. The clones were selected based on the distribution of Oidium leaf disease of each clone and suggested by MRB.

2.3 Data Pre-Processing and Processing

This stage is a crucial part of the study where the data needed to be handled and process properly cause it can affect the final output of this study. The error produced in this stage is necessary to be at a minimum level as it will not affect the final result.

2.3.1 UAV

Orthophoto image is the result of UAV data processing that consists of mosaicking and layer stacking. The aerial image derived from the camera is selected carefully to reduce error while processing the image. Mosaicking is a technique for tiling digital image for image processing. In order to produce a large radiometrically image, the mosaicking blends the arbitrary images to ensure that the boundaries between the original images were not visible.

Next, layer stacking was conducted to segregate each band for each image to collect their digital number. This process is necessary as it will provide a better basis for data comparison between images taken by different sensors. Moreover, this will align the result between the aerial image and the value of spectroradiometer. The output of this process was an image with four band combination which is blue, green, and red from visible image and blue band from the near-infrared image.

2.3.2 Spectroradiometer

The spectroradiometer observation technique has been widely used to evaluate the availability of the canopy variable such as ground biomass and the canopy chlorophyll content for remotely sensed spectral data. Using spectroradiometer, as theoretically crop in good nutritional condition has high reflectance in the visible region and near-infrared region. The spectral reflectance of the respective leaves was observed 10 times using the spectroradiometer. The mean spectral reflectance for healthy, unhealthy, and severe infection of Oidium leaf disease is shown in Fig. 3.

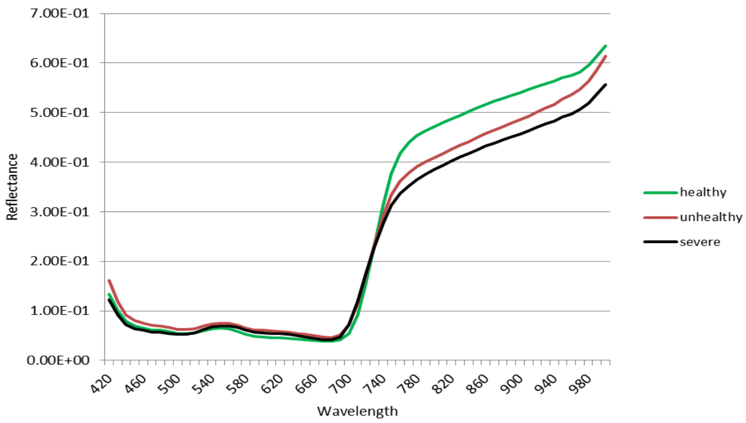


Fig. 3 - The mean spectral reflectance for healthy, unhealthy, and severe infection of Oidium leaf disease

2.3.3 Extraction of Vegetation Indices

Vegetation indices (VIs) are usually developed to extract vegetation information based on two or more spectral bands [15]. The VIs is designed to increase the sensitivity of spectral features related to a biophysical variable of interest while reducing confounding factors such as external effects like sun angle, viewing angle, and atmospheric composition, as well as internal effects like topography, soil variations, and differences in senesced or woody vegetation [26]. VIs is one of the basic approaches to analyze remote sensing data and have been introduced in phenotyping of biomass, greenness studies, nitrogen content, pigment composition and also photosynthetic [16]. The main reason to adopt these indices was to distinguish disease mapping for rubber plantation. Table 1 shows the wavelengths used to derive the indices.

Table 1 - List of Vegetation Indices deploy in this study

Index	Formula
Normalized Difference Vegetation Index (NDVI)	$\frac{(NIR - RED)}{(NIR + RED)}$
Soil-Adjusted Vegetation Index (SAVI)	$\frac{(NIR - RED)}{(NIR + RED + L)} + (1 + L)$
Ratio Vegetation Index (RVI)	$\frac{RED}{NIR}$
Greenness Vegetation Index (GVI)	$\frac{GREEN}{NIR}$
Global Environment Monitoring Index (GEMI)	ή x (1 – 0.25 x ή) – [(RED – 0.125) / (1 – RED)] where ή = [2*(NIR^2 - RED^2) + 1.5 x NIR + 0.5xRED] / (NIR + RED + 0.5)

3. Results and Analysis

The results generated were used to identify the physical condition of the rubber tree based on several samples randomly collected. Results derived from the digital compact camera payload on UAV and handheld spectroradiometer were analyzed by comparing the trend of the graph based on healthy, unhealthy, and severe infection of Oidium leaf disease.

3.1 UAV Spectral

Generally, the spectral output from the UAV was derived from the digital compact camera. The UAV images have been generated into two orthophotos which are composite band RGB and NIR. In order to show the result of the digital number obtained from the orthophotos, the data information was applied for healthy, unhealthy and severe infection is used. Figure 4 shows the DN values for healthy in the blue, green, red, and near-infrared wavelength.

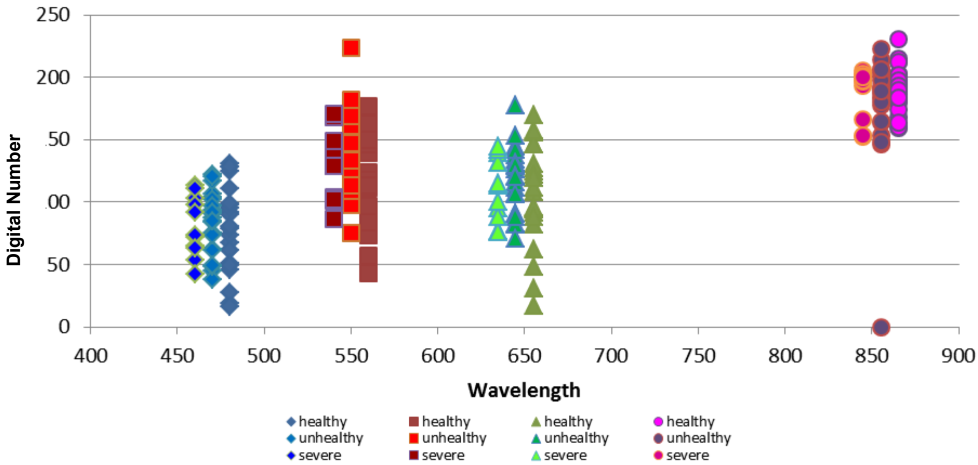
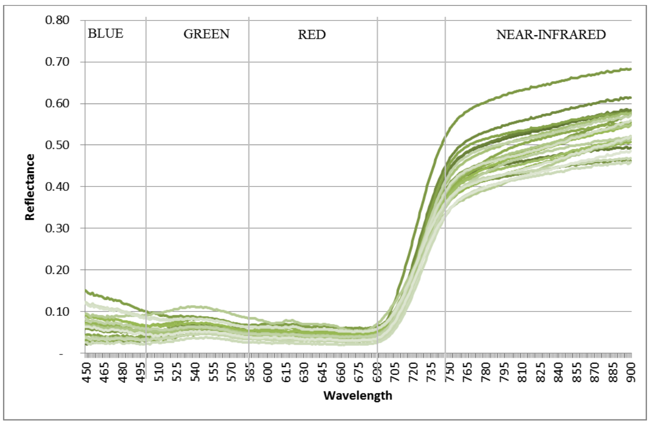


Fig. 4 - The DN values for healthy, unhealthy, and severe infection at the blue (480), green (560), red (655) and near infrared (865)

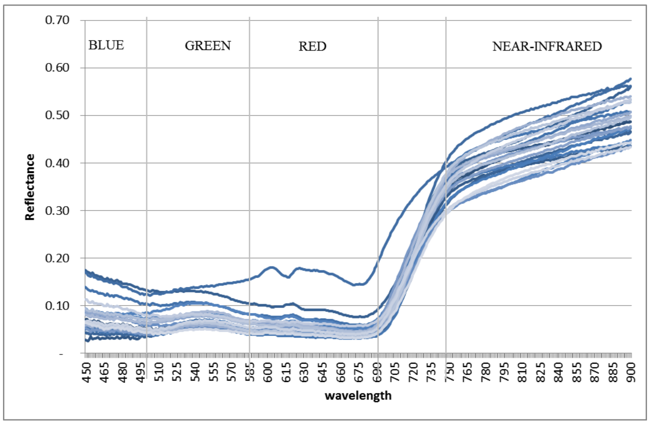
3.2 Spectroradiometer Spectral

The spectral reflectance obtained by spectroradiometer based on healthy, unhealthy, and severe infection of Oidium leaf disease is shown in Fig. 5. In general, healthy vegetation absorbs most of the red light while little near infrared light from the sunshine for photosynthesis. Therefore, the sensor above the crop will receive a very little reflection of red light whereas most of the near-infrared light is reflected. This can be seen in Fig. 5(a) where reflectance in the red band is less than 10% as compared to the near infrared band with more than 50% reflectance.

On the other hand, stressed vegetation often has less chlorophyll and appears to be yellowish and can be detected by decreasing of red-light absorbance and near-infrared reflectance. A similar trend showed by the unhealthy and severe infection of rubber leaf in Fig. 5(b) and Fig. 5(c).



(a)



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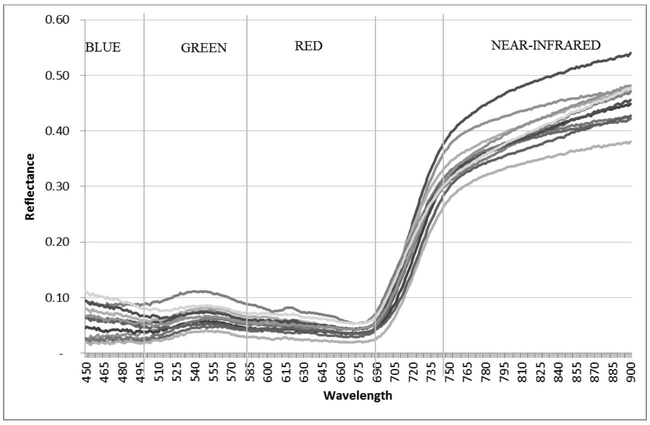
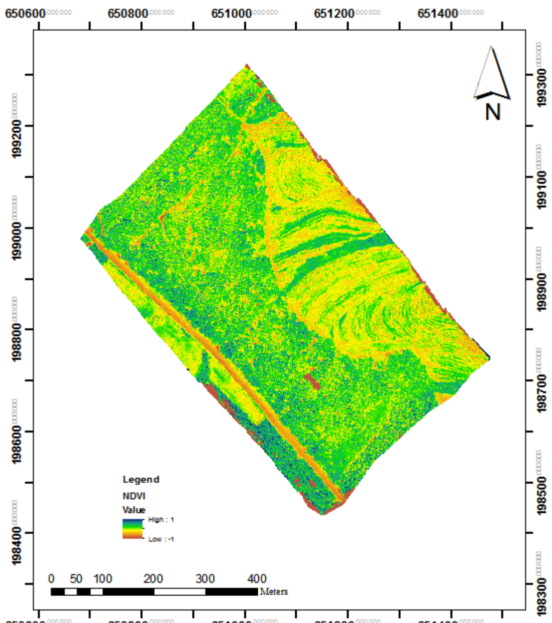


(c)

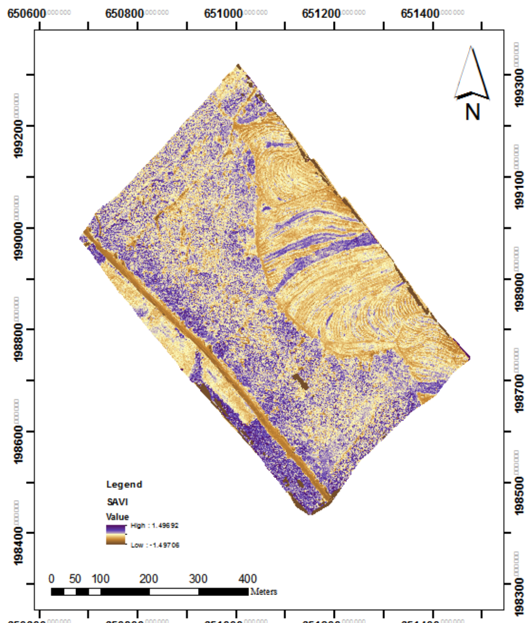
Fig. 5 - The spectral curve of rubber tree leaf using spectroradiometer (a) healthy; (b) unhealthy and; (c) severe infection

3.3 Spectral Vegetation Indices

Five vegetation indices (VIs) were used, such as: normalized difference vegetation index (NDVI), soil adjusted vegetation index (SAVI), ratio vegetation index (RVI), green vegetation index (GVI), and global environmental monitoring index (GEMI) respectively as shown in Fig. 6.



(a)



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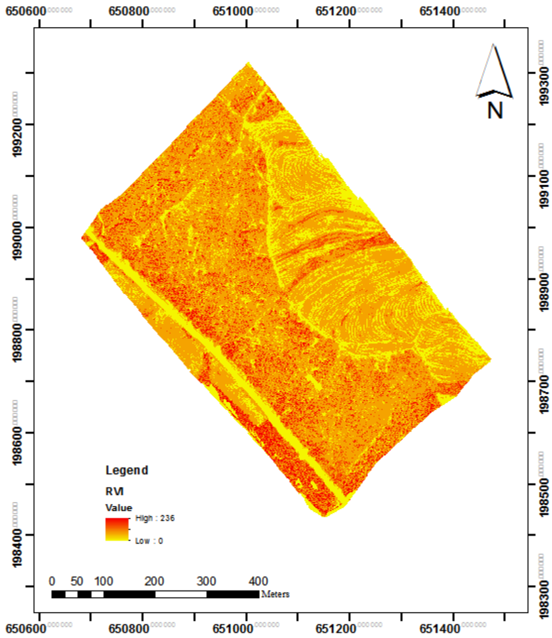
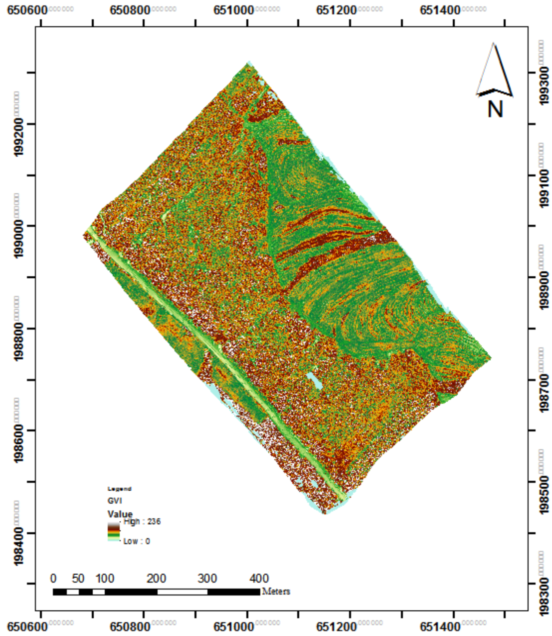


(c)



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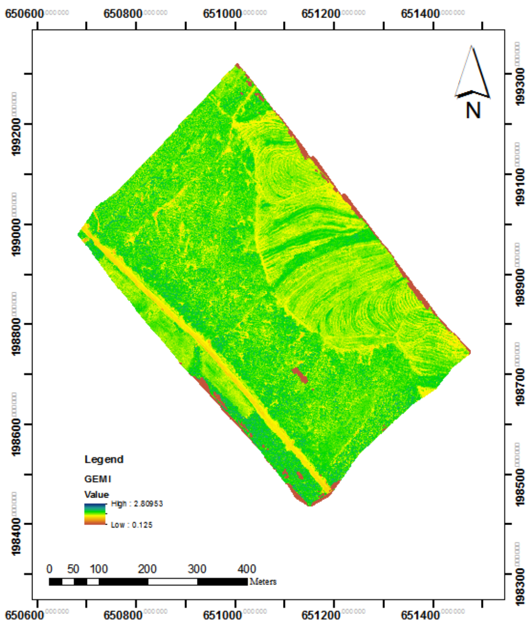


(e)

Fig. 6 - Vegetation indices that used (a) normalized difference vegetation index (NDVI) map; (b) soil adjusted vegetation index (SAVI) map; (c) ratio vegetation index (RVI) map; (d) green vegetation index (GVI) map and; (e) global environmental monitoring index (GEMI) map

3.4 Regression Model

For regression analysis, total of 15 samples were randomly selected based on a healthy and unhealthy leaf while 8 samples for severe infection. The result of regression analysis is shown in Table 2 which are three models generated according to healthy, unhealthy, and severe infection of Oidium leaf disease.

A healthy, unhealthy, and severe map is created regarding to the model generated using the regression model. The map is generated from the UAV images by implementing the equation into the image. The produce map will illustrate whether the area is prone to Oidium leaf disease infection or free from disease.

Fig. 7 shows that the healthy area value ranging from 0.275 (healthy) to -0.1196 (unhealthy). Based on the map, the area was indicated as healthy area due to the value of the area is more than 0.128804.

Table 2 - Regression statistic result for the generated model

Source	Obs.	Parameter	Regression model	R^2	F-value
Healthy	15	RED vs NDVI	$y = 0.1857x^2 - 0.1859x + 0.0739$	0.66	4.36^{*}
Unhealthy	15	RED vs GEMI	$y = 6.7688x^2 - 24.773x + 22.705$	0.68	11.05^{**}
Severe	8	BLUE vs SAVI	$y = -0.3809x^2 + 0.001x + 0.071$	0.76	13.53^{ns}

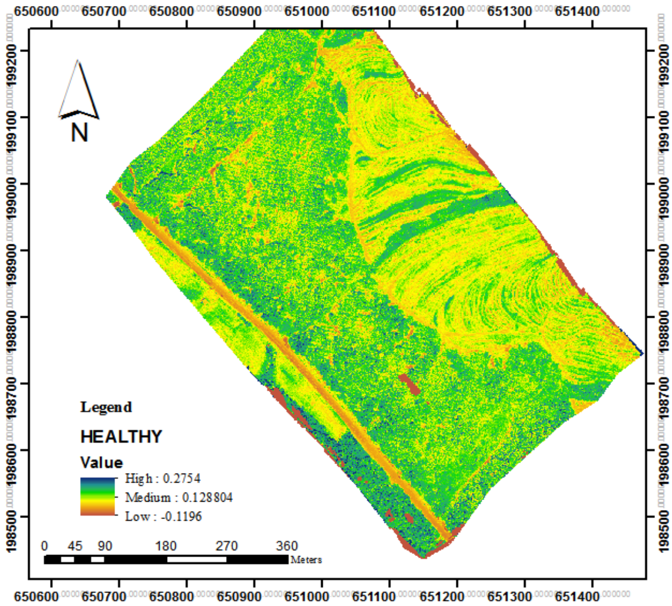


Fig. 7 - A healthy map for rubber plantation

The unhealthy map shows that the highest value is 19.6084 and the lowest value is -46.8956 as shown in Fig. 8. Based on the map, the study area was indicated as a healthy area as the value is less than -22.3086. The severe map Fig. 9 shows that the study area has a low value that is 0.0698. Although there are several samples that were identified with a severe infection of Oidium leaf disease, the severe map has indicated that the area was not affected by the disease. In addition, the study area was well managed with regard to agronomic practice and controlling of pest and diseases as the area was an experimental area for MRB.

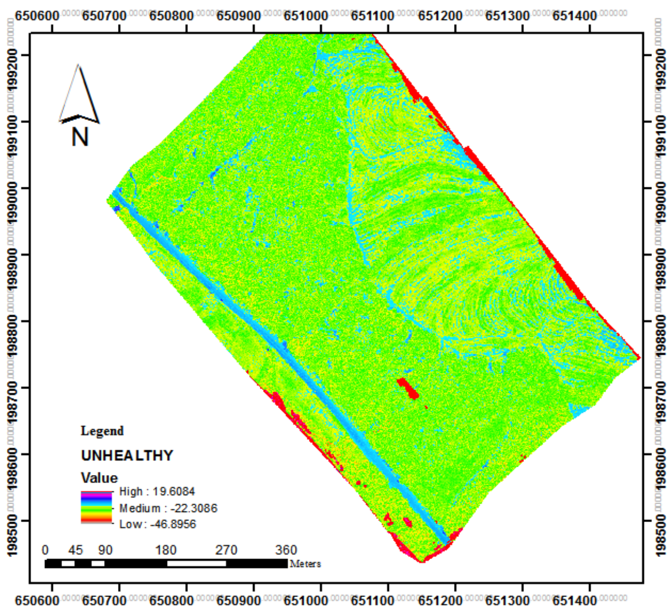


Fig. 8 - An unhealthy map for rubber plantation

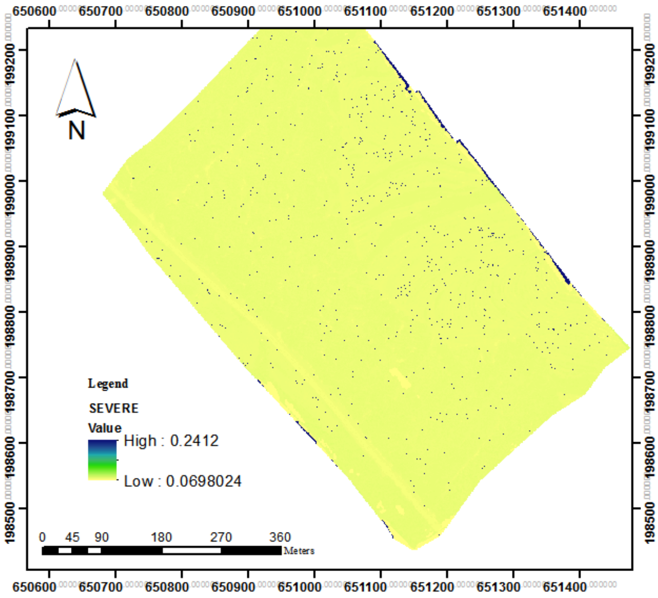


Fig. 9 - A severe map for rubber plantation

3.5 Quantitative Analysis

Quantitative analysis often deals with the collection and data analysis in the numeric forms which tend to highlight relatively large scale and representative sets of data. In this study, the value of spectral and estimated spectral are analysed using f-test and RMSE. The number of samples used for healthy, unhealthy, and severe is 7, 8 and 3 respectively. The statistical analysis of the estimated spectral using generated model is shown in Table 3.

Table 3 - Statistical analysis of the estimated spectral using generated model

Source	Healthy		Unhealthy		Severe	
	S	ES	S	ES	S	ES
Mean	0.114	0.039	0.0631	-21.434	0.0707	0.071
Variance	0.00114	0.00004	0.0018	1.026	0.00	0.00
Observations	7	7	8	8	3	3
df	6		7		2	
f-value	2.887*		0.002*		1.008	
Critical one tail	4.283		0.264		0.0526	
RMSE	2.89		-0.0029		1.009	

S – Spectral, ES – Estimated Spectral, RMSE – Root Mean Square Error

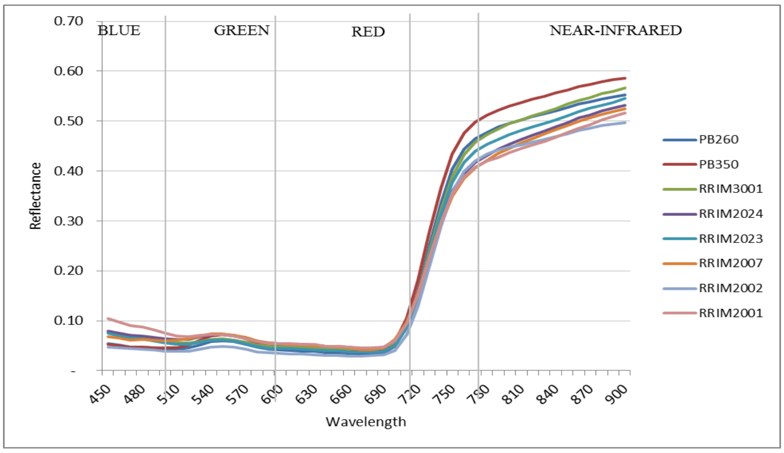
Table 3 shows that the f-value is smaller than Critical-one tail for healthy, unhealthy while for severe the f-value is larger than Critical-one tail. In this case, the f-value is $2.887 < 4.283$ (healthy), $0.002 < 0.264$ (unhealthy) and $1.008 > 0.0526$. Thus, this can be concluded that spectral and estimate spectral population is equal at the 0.05 significant levels.

3.6 Qualitative Analysis

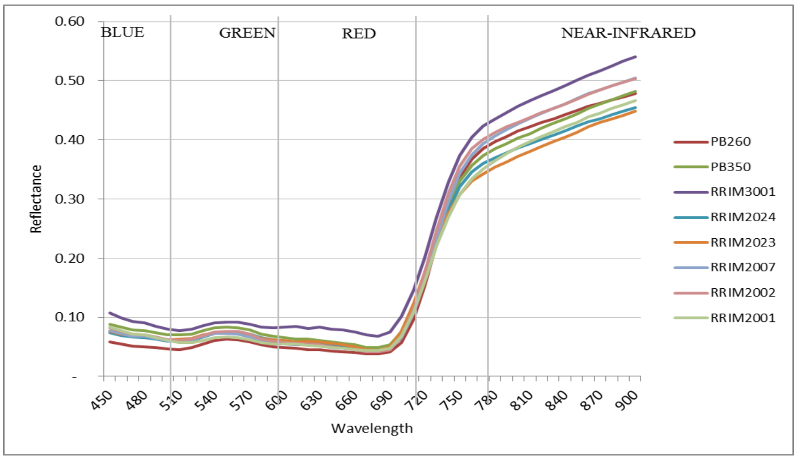
In order to precede the qualitative analysis, the spectral of rubber clones planted in the study area were used. A total of eight clones were selected which are PB 260, PB 350, RRIM 2001, RRIM 2002, RRIM 2007, RRIM 2023, RRIM 2024 and RRIM 3001. Fig.10 illustrates the spectral of each clone based on healthy, unhealthy, and severe infection.

Referring to Fig.10, each clone can be distinguished at the near infrared band for healthy, unhealthy, and severe respectively. Clone RRIM 350 shows the highest reflectance in the NIR band for a healthy group. This clone has rounded shape of a leaf with overlapping characteristics reflects more NIR light as compared to the other clones. For the unhealthy group, clone RRIM 3001 shows the highest reflectance in the NIR band. The leaf characteristic is an elliptical shape with separated leaflets. Clone PB 260 shows the highest reflectance in the severe group at NIR band. The leaf is the broad elliptical shape and overlapping thus was easier to identify if the leaf was affected by the disease.

According to MRB (2013), clone PB 260 has a medium infection of Oidium leaf disease which leads to the highest reflectance of the NIR band.



(a)



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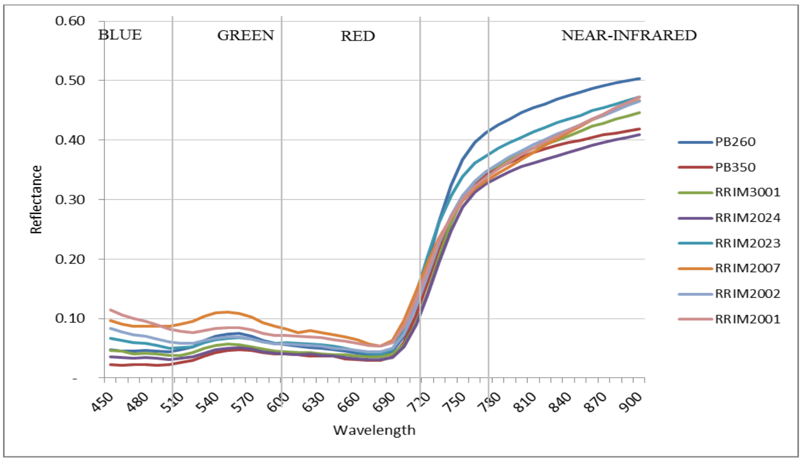

(c)

Fig. 10 - Spectral reflectance for rubber clones for (a) healthy; (b) unhealthy and; (c) severe infection of Oidium leaf disease

4. Conclusion

It can be concluded that rubber leaf with a healthy, unhealthy, and severe infection of Oidium leaf disease can be identified and monitored by using low altitude remote sensing technology which is an unmanned aerial vehicle (UAV) and non-matrix digital compact sensor. The implementation of UAV platform in this study can reduce the manpower needed and reduce the budget allocated significantly. In addition, UAV is able to provide real-time data without consuming too time and anyone can operate the UAV by mastering how to operate UAV. Mohidem et al. [27], believe that the present trend of improving UAV sensor quality and user friendliness will continue and eventually allowing non-expert users to use RGB, multispectral, hyperspectral, and thermal sensors on a regular basis. Furthermore, this study can be used as a guide in the early stage for agencies that related to this field in order to minimize the diseases outbreak that might occur at the rubber tree plantation. Besides that, the method used in this study is more user friendly and involving low-cost advanced technology which is suitable for smallholder and related agencies.

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