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Peak Detection Image Processing Algorithm for Qualitative Analysis of Oil Palm Trees

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ABSTRACT

Oil palm has tremendous potential for the economic development of the country, therefore it is imperative to have accurate and reliable information, especially concerning plant quality, phenology, and health and yield prediction. The most important limitations for decision making are the lack of data, cost effectiveness and timely processing of information. The innovation in technology, such as Remote Sensing (RS) has modernized the conventional methods and recognized as a modern agriculture crop information provider tool for worldwide oil palm stakeholders. The aim of this study is to design and implement peak detection image processing algorithm, as an approach to the qualitative analysis of oil palm trees, discriminate between the stressed and healthy oil palm trees identified through the aggregate value samples in visible, near infrared and shortwave infrared region for individual oil palm crowns. Subsequently detect the stressed and dead oil palms by analyzing the values in the near infrared and a shortwave infrared region. The algorithm applied on AISA Classic and AISA Eagle images and analyzed by the remote sensing image processing software Environmental Visualization of Images (ENVI 4.7) and Interactive Data Language (IDL 7.1). The results show that the algorithm can be functional for the better planning of oil palm plantation.

KEYWORDS: oil palm; remote sensing; peak detection; algorithm; image processing

1. INTRODUCTION

Tropical rain forests represent some of the most biologically diverse, structurally complex ecosystems on earth. The identification of tree species is a key element in the definition of habitats of key fauna that use specific trees for food and shelter. Remote sensing is beginning to play a more active role in the efforts to detect, monitor and manage forests and individual tree. Monitoring individual tree health and stress from remotely sensed images is of concern for forest management. The art monitoring system aimed at tree species identification using airborne and the spaceborne sensors are potentially key tools for the development of sustainable development policies. Oil palm (*Elaeis guineensis Jacq*) is an inhabitant of the coastal swamplands, and freshwater rivers of central and West Africa. There are large-scale plantations of oil palm throughout the tropics, especially Malaysia and Indonesia, which are major producers. Demand for palm oil is raising and expected to climb further, particularly for the use of biodiesel; it is promoted as a form of renewable energy that greatly reduces next emission of carbon dioxide into the atmosphere, and decreases the impact of greenhouse effect [1]. The major threat to sustainable oil palm production is the *Ganoderma boninense* disease, which causes extensive damage to the oil palm. In this regards a technique developed [2] based on vegetation indices and red edge; however, the accuracy of the results achieved was not very high, being between 73% and 84%. Airborne hyperspectral remote sensing can be used as an efficient tool in monitoring the characteristics of oil palm plantation in order to predict and manage the oil palm production by using a new image processing techniques.

The innovation in technology, such as Remote Sensing (RS) and Geographic Information Systems (GIS), has modernized the conventional methods. Remote sensing is recognized as a modern agriculture crop information provider tool for worldwide oil palm stakeholders. One of the important characteristics of Hyperspectral sensors is the spectral resolution, which provides unique spectral signatures for trees and other natural and man-made objects. Spectral signatures show the amount of solar radiation absorbed, reflected, transmitted and emitted with different wavelengths as a distinctive curve. These phenomena allow the accurate classification of the oil palm plantation according to health and stress. A variety of remotely sensed data is available from a wide range of sensors and various platforms like multispectral and hyperspectral. Advances in sensor system technology, however, have effectively removed one of the most significant barriers of multispectral remote sensing, that is, the limitation of spectral dimensionality. Hyperspectral remote sensing has the potential to measure specific vegetation variables that are difficult to measure by traditional multispectral sensors. AISA-classic is one of the most significant sensors. The Airborne imaging spectrometer is extensively used for mapping applications and provides flexible operations under cloudy and variable skies.

One of the foremost requirements for the growth of oil palms is the nutrients. If there is a deficiency of any nutrient in the oil palm it can identify by leaf analysis [3]. For the examination of nutrients in oil palm [4] expressed that remote sensing data alone are inadequate for measurement, it also requires data analysis tools for laboratory observation, and,

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finally, to identify the relationship between the laboratory data and sensor data. The focal intention of the study, which was carried out in Sungai Papan Estate, Kota Tinggi, and Johor, was to develop a model for quantifying nitrogen levels in oil palm leaves by using Landsat TM data. In this study a radiometric corrected Landsat-5 TM satellite image, digital map of the fertilizer trail plot and analysis data were used. ERDAS Imagine version 8.3.1 image processing software was used for atmospheric correction. Although the use of the remote sensing technique for the extraction of nutrients is faster and low cost, it is still only at an initial stage and necessitates a lot of work. The study, however, is more efficient and advanced if high-resolution hyperspectral images are used.

Fungal disease detection in perennial crops is a major issue in estate management and production. However, nowadays such diagnostics are long and difficult when only made from the observation of visual symptoms, and very expensive and damaging when based on a root or stem tissue chemical analysis. As an alternative, [5] developed a tool to evaluate the potential of hyperspectral reflectance data to detect the disease efficiently without the destruction of tissue. This study focuses on the calibration of a statistical model of discrimination between several stages of *Ganoderma attacks* on oil palm trees, based on field hyperspectral measurements on tree scale. A combination of preprocessing, partial least square regression and linear discriminate analysis is tested on about hundred samples to prove the efficiency of the canopy.

Spectrally continuous hyperspectral remote sensing data can provide information on forest biochemical contents, which are important for studying vegetation stress, nutrient cycling, productivity and species recognition, etc. Remote sensing measurements have the potential to provide a cost effective means to examine the complexity of forests and generalize findings from the plot scale. The introduction of hyperspectral sensors produces much more complex data and provides much enhanced abilities to extract useful information from the conventional data stream. However, it also demands more complex and sophisticated data analysis procedures if their full potential is to be achieved. Hyperspectral technology and imaging spectrometry technology are as being among the important leading research fields of remote sensing [6]. Research on processing, analysis and information extraction of hyperspectral data should be strengthened to determine more useful information, and make full use of the advantages and potential of hyperspectral remote sensing technology, and promote the development of new and vital technology [7, 8].

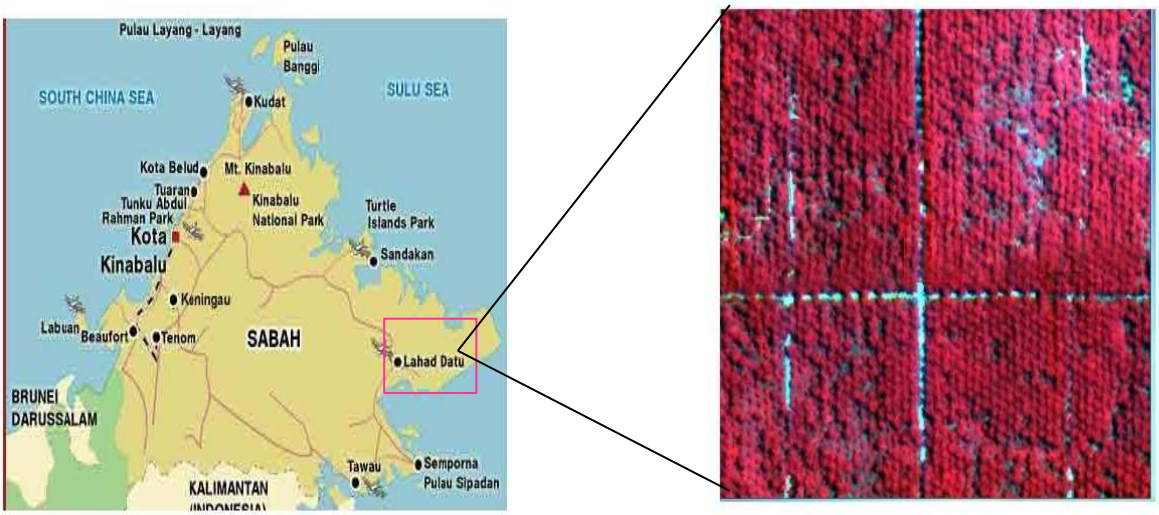
Digital image processing is an expanding area with applications regarding to our daily lives. Various tools and methods are used for image processing, data analysis and classification. Scientists and practitioners have made immense efforts to build up advanced approaches and techniques for improving accuracy [9]. Remote sensing software is exceedingly functional to manipulate geospatial data; therefore, image processing software offers a viable solution to access that data in an easy way and distribute new data to the extensive users. Several algorithms have been developed for diversifying functions in image processing, depending upon expert knowledge about the characteristic of interest in the data. Many image processing and analysis techniques have been developed to aid the interpretation of remote sensing images and to extract as much information as possible from the image. Remote sensing and Geographic information system (GIS) are very significant tools, that can provide crucial information to various fields such as Army, agriculture, environmental, transportation, medicine, industries, forestry and etc [10]. The aim of this study is to design and implement a practical and productive peak detection image processing algorithm, as an approach for the stress detection of oil palm trees. AISA Classic and AISA Eagle image have been analyzed by using ENVI and IDL. AISA systems have been chosen in the research because they are user friendly, easy to install and remove from any aircraft, and provide timely, accurate and reliable information.

2. MATERIAL AND METHOD

2.1. Study Areas and hyperspectral data

In this research two areas in Malaysia were selected as the study areas. The first study area is Lahad Datu, Tawau Division Sabah eastern Malaysia. Figure 1 shows the study area (Lahad Datu) and the hyperspectral airborne image used in the study. The image was acquired by using UPM-Advance Imaging Spectrometer for Application (AISA-Classic) sensor, which is light weight and can easily be installed in an aircraft such as the ShortSC7-SkyVan. The sensor is a very compact push broom system, with sensor head, a miniature GPS/INS data acquisition unit and caligeo post processing system. The sensor is capable of collecting data within a range of VIS/NIR 430-900 nm, up to 286 spectral channels and with a fine 1.8 nm spectral resolution. The spatial resolution of the data is 1m with 1000m flying altitude. The airborne image was acquired in May 2006, between 10 am and 2 pm over Lahad Datu Sabah. The map projection is Universal Transverse Mercator UTM zone 50 North, with a latitude of 5° 24’ 29.44” N and longitude 119°11’14.98” E, and datum World Geodetic System WGS-84. The hyperspectral image of the research area is a False Color Composite (FCC) image 1133x750x20 unsigned integer; band sequential (BSQ) with the default bands.

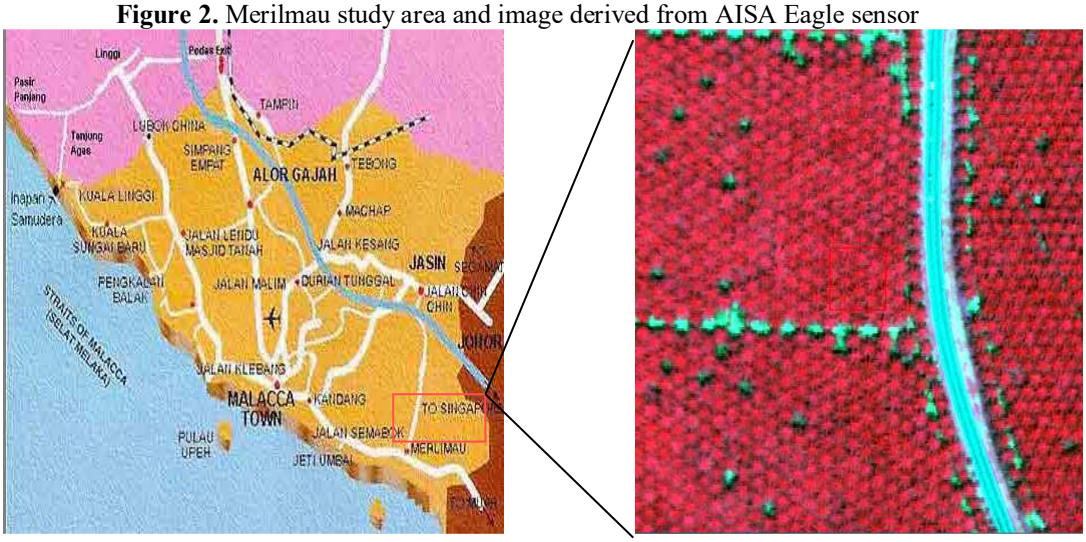
Figure 1. Lahad Datu study area and image derived from AISA Classic sensor



The second study area used in this research is Merilmau, a town in Melaka, Malaysia. Figure 2 indicates the second study area and the hyperspectral airborne image used in the study. The image was acquired performance, 244-channel hyperspectral imaging system known as AISA Eagle. It provides cost effective, end-to-end airborne collection capabilities that acquire research grade spectral imaging data for use in military, environment and commercial remote sensing programs. The sensor operates across the VIS/NIR portion of the spectrum (400-1000nm), resolving spectral difference as fine as 2-4 nm with 1000 pixels per scanning line. The map projection is Universal Transverse Mercator UTM zone 48 North, with a latitude of 2º 11' 51.72" N and longitude 102º26'17.71" E, and datum World Geodetic System WGS-84. The AISA Eagle image of research in that area is FCC image with 709x513x128 (samples, lines and bands) unsigned integer; band sequential (BSQ) with default bands.

The images exhibit outside the visible range of electromagnetic spectrum; therefore, the vegetation is displayed in red color, urban areas in cyan and soil in light brown color. All other shades are based on leaf structure, moisture content and the health of the plant. After image acquisition the data was preprocessed to remove all distortion, artifacts and noise. After preprocessing, the feature extraction technique is used to detect the main regions of interest from the AISA image. In this phase the image is organized into distinguished components and training areas according to their feature characteristics. The main purpose is to sort out the pixels in an image into different land cover classes and analyze the image according to reflectance absorption in the visible band, near infrared band (NIR) and Shortwave infrared (SWR) region.

Figure 2. Merilmau study area and image derived from AISA Eagle sensor



2.2. Peak detection image processing algorithm

For qualitative analysis the algorithm largely depends upon the previously conducted FBE studies. Using SCC as a reference point, analysis was carried along the NIR and SWR of the electromagnetic spectrometer. Traditionally, researchers have focused on the Foliar Biochemical Estimation (FBE) and with the use of finer spectrographic have been able to identify the spectral signatures that define the stress levels in vegetation using the near infrared regions (NIR) of the electromagnetic spectrometer.

The growth status of vegetation can be identified by the indication of chemical concentration of different nutrients in the crop. The common factor to estimate crop yield is to monitor real time changing detection in chemical concentration. Since Hyperspectral sensors measured in contiguous, narrow band spectral analysis therefore the reflectance and absorption features related to specific crops can be detected from the spectral profile. Spectral analysis techniques provide versatile methods for the different applications including agriculture, forestry and vegetation. It can compare the absorption and reflectance features present in the spectrum. On the basis of an in-depth study concerning the health of the oil palm trees [11] expressed that image spectral reflectance signatures indicate the physical characteristics of the oil palm. The most imperative characteristics of vegetation are the absorption of light in the visible part of the spectrum and strapping reflectance at the wavelength above 700nm.The red edge phenomenon specifies the rapid amendment in the reflectance of chlorophyll and reveals the status of vegetation in near infrared range [12].

Peak detection image processing algorithm has been developed to monitor the health and stress status of individual oil palms. In this regards discriminate between the stressed and healthy oil palm trees identified through the aggregate value samples in the visible, near infrared and shortwave infrared region for individual oil palm crowns. Subsequently detect the stressed oil palms, which have been categorized into three classes (S1, S2, and S3) according to their stress condition. The slightly stressed oil palms have been categorizes as S1, moderately stressed as S2, and severely stressed as S3. Finally identify individual dead oil palms by analyzing the values in the visible, near infrared and shortwave infrared region. The healthy oil palm trees have higher reflectance between 700-900 nm because of the higher concentration of chlorophyll in the fronds and NIR is greater than SWR.

$$Healthy\ Tree\ = Visble\ > NIR\ and\ SWR$$

$$Dead\ Tree\ = Visible\ < NIR\ and\ SWR$$

$$Stressed\ Tree\ = Visible\ more\ > NIR\ and\ SWR$$

However, the stressed trees seem to have a lower level of chlorophyll and mineral deficiency, which leads to a decrease in the spectral reflectance of the leaves in the range of 450-500, and NIR, is less than SWR. This reflectance increases with the varying levels of stress in the vegetation. Dead oil palm trees have the lowest spectral reflectance due to the lowest moisture control in the NIR portion of the electromagnetic spectrum. Referenced studies show that in comparison to the healthy trees where SWR is less than NIR, in the dead trees it inverse, as shown in Figure 3 and Figure 4 respectively.

Figure 3. Indicates the Visible Higher than Near Infrared and Shortwave Infrared Region in Healthy Tree Spectral Signature

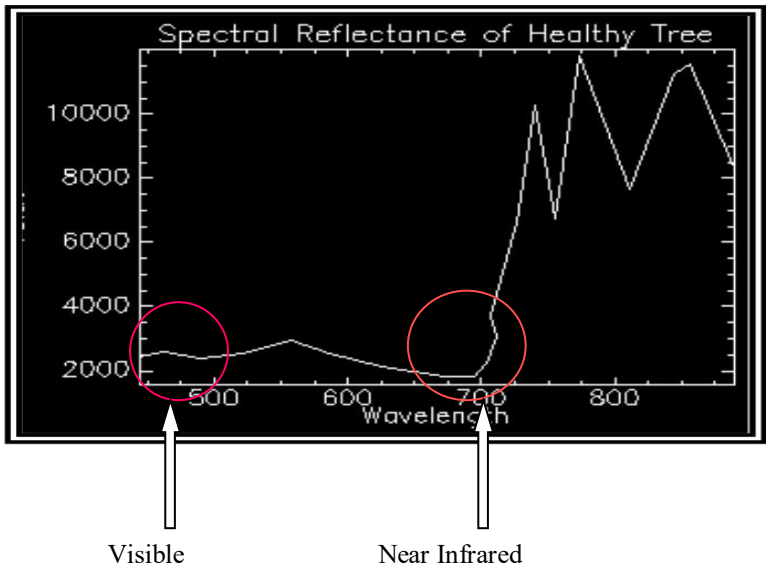
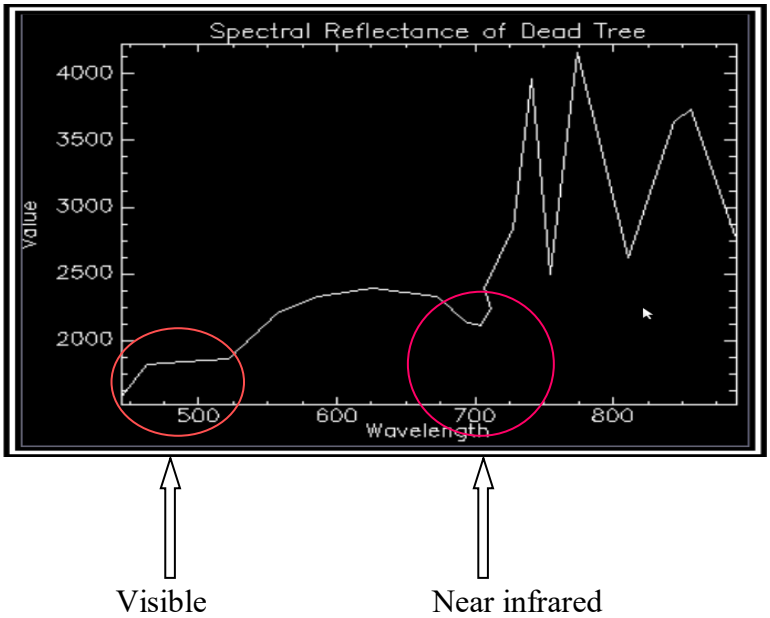


Figure 4. Indicates the Visible lower than Near Infrared and Shortwave Infrared Region in Dead Tree Spectral Signature



The assessment of the stress levels of a tree is measured against the predefined levels of visible and NIR readings on a spectrograph. Presently, these levels are taken as a symbolic value for programming purposes only in order to be able to demonstrate the application's capability for identifying the different stress levels of the trees. When analyzing the spectral properties of a plantation, the reflectance of water bodies is significant in the identification of dead trees within the region having high vegetation indices reflection. A tree, while having a highly reflective canopy will typically overshadow the reflectance of the soil water, whereas the region of a dead tree will continue to display a high value for soil water reflectance shortwave infrared SWR in the spectrograph. The difference between the healthy and stress levels in the visible and near infrared region can be observed Figure 6.

Figure 5. Indicates stressed oil palm tree level in Visible and NIR region

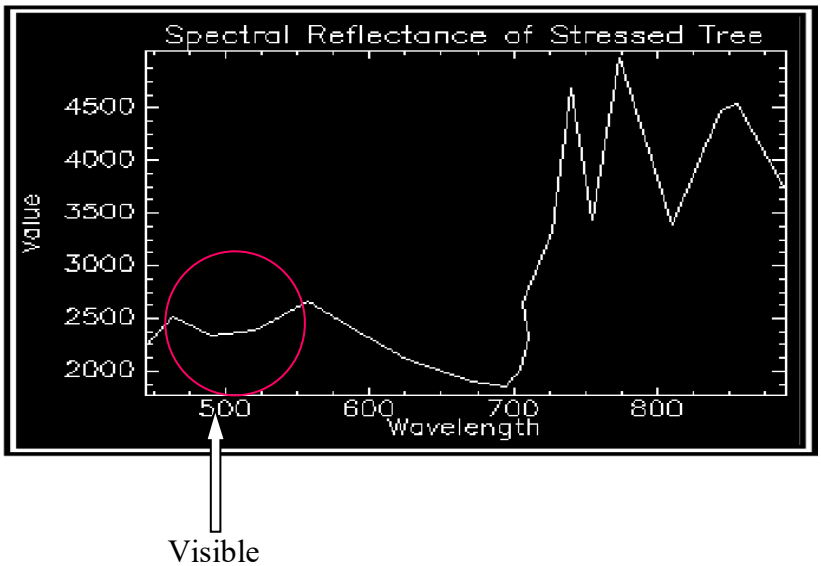


Figure 6. Aggregate values indicates oil palm health

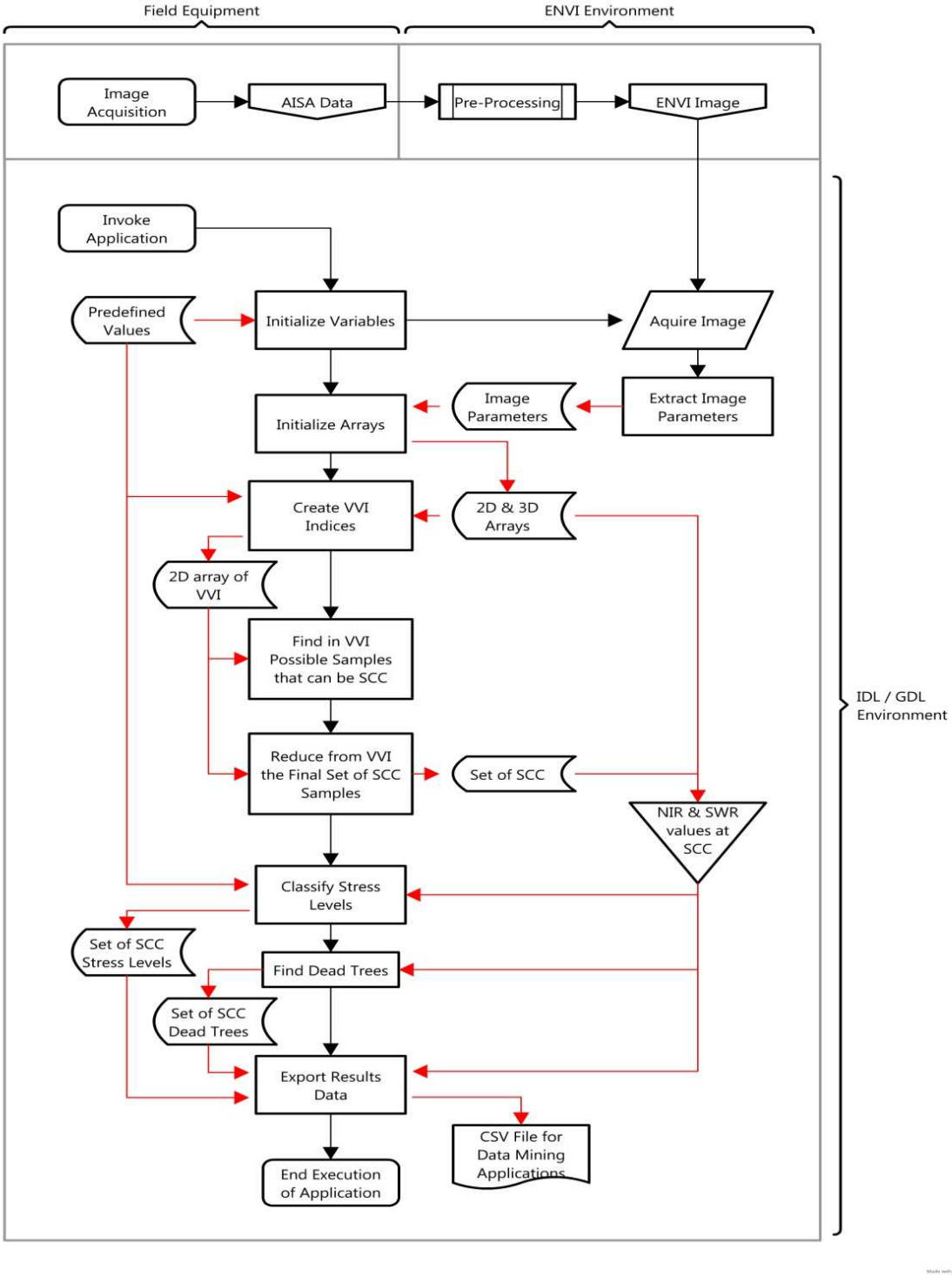
0	0	1	0	0	0	0	0	0	1	0	0	0	0
0	1	2	2	1	1	0	0	2	3	3	2	1	0
0	2	6	6	6	2	0	0	3	8	8	7	3	0
1	3	7	8	7	3	1	1	4	8	9	8	4	0
1	3	6	3	7	2	0	1	4	8	6	8	3	0
0	2	3	3	2	1	0	0	3	4	4	3	1	0
0	0	1	1	0	0	0	0	0	1	1	0	0	0

Figure 7. Major Steps Involve in peak detection image processing algorithm

```
  Initialize variables for individual tree SCC, healthy tree H,
  Slightly stressed S1, moderately Stressed2 S2, severely Stressed S3
  and dead tree D.
begin
        Initialize Arrays
        Find VVI possible samples that can be SCC
if SCC located  then
        Identified and count as an individual tree.
else
        Non vegetated Area.
        begin
        Set threshold values for H,
        Set threshold values for S1,
        Set threshold values for S2,
        Set threshold values for S3
        Set threshold values for D.
        Identified and count H, S1, S2, S3, and D.
        end
        Compute and Export results in CSV format.
end
end
```

The major steps involved in the algorithm are described in Figure 7 and further explained in flowchart illustrated in Figure 8. The black arrows represent the flow of the code while the red arrows indicate the memory variables set recalled in the different sections of the application.

Figure 8. Flowchart describe peak detection image processing algorithm; the black arrows represent the flow of code while the red arrows indicate memory variables Set recalled in the different Sections of the application



In order to automate the process, the algorithm is implemented in the IDL code, which analyzes the AISA Classic and ASA Eagle image, and demonstrates the calculated results. The peak detection algorithm software application developed imports the ENVI data into IDL variables and delivers (converting the sample indices according to IDL standards) and outputs the result in text and comma Separated Values (CSV) format, which can be utilized by any data mining application for further analysis in future.

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3. RESULTS AND DISCUSSION

The AISA Classic and AISA Eagle images have been examined according to parameters are set according to these regions of interest and applied in the IDL source code. The whole AISA Classic image is very large, consists of 1,133 Samples, 750 lines and occupies approximately 85 ha.The AISA Eagle image comprises 709 samples, 401 lines and occupies 36 ha area. First the seven spatial subsets of the AISA Classic image (ACSS1-ACSS7) as shown in Figure 9 and Figure 10, were taken and analyzed using the peak detection image processing algorithm in IDL. Finally, the whole AISA Classic image analyzed.

Figure 9. Gray scale AISA Classic image indicates the randomly selected spatial subsets

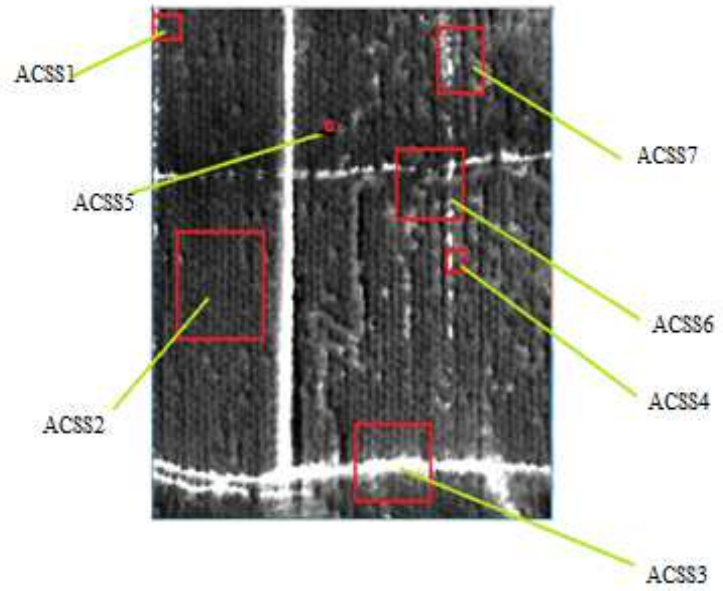
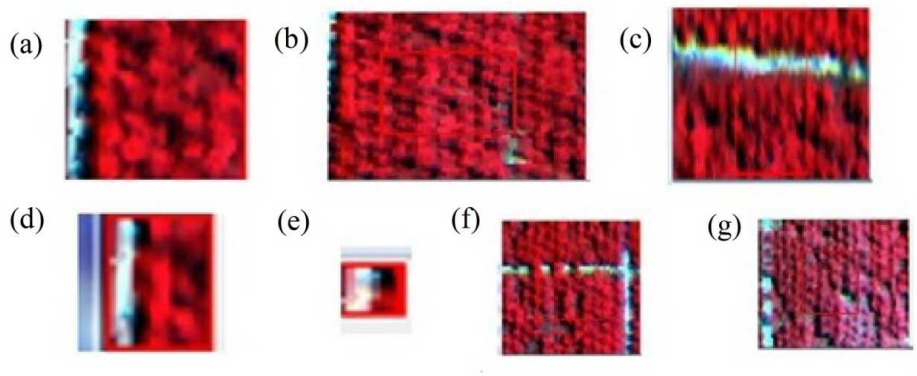


Figure 10. AISA Classic image selected spatial subsets (a) ACSS1, (b) ACSS2, (c) ACSS3, (d) ACSS4, (e) ACSS5, (f) ACSS6, (g) ACSS7



Similarly the seven spatial subsets of the AISA Eagle image (AESS1-AESS7) as shown in Figure 11 and Figure 12, were taken and analyzed using the peak detection image processing algorithm in IDL. Finally, the whole AISA Eagle image analyzed.

Figure 11. Gray scale AISA Eagle image indicates the randomly selected spatial subsets

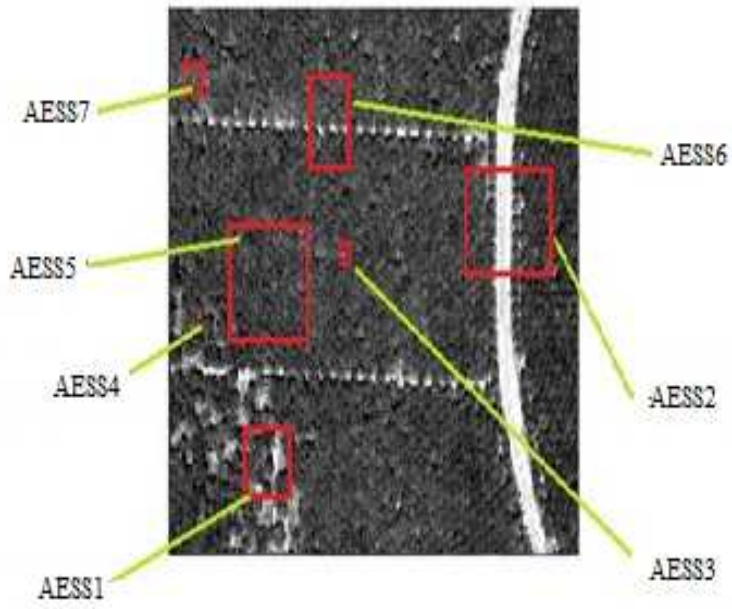
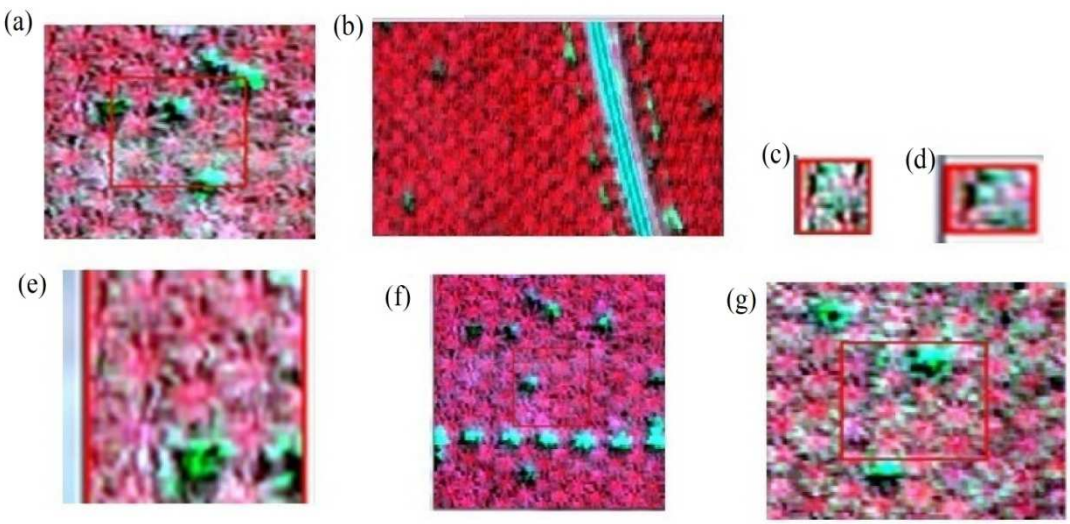


Figure 12. AISA Eagle image selected spatial subsets (a) AESS1, (b) AESS2, (c) AESS3, (d) AESS4, (e) AESS5, (f) AESS6, (g) AESS7



In the qualitative analysis of the oil palm trees; the health and stress status of each oil palm was analyzed. The individual oil palm tree (TC) in AISA Classic image and AISA Eagle is located according to the peak detection at the X-coordinate at X-axis as X-cord and Y-coordinate at Y-axis as Y-cord. The Health Status (HS) is categorized into different classes, which indicates a dead tree as “D”, a healthy tree as “H”, and a slightly stressed oil palm as “S1” moderately stressed as “S2” and severely stressed as “S3”.

The AISA Classic image spatial subsets (ACSS) results are described in Table 1. In the ACSS1, 34 healthy oil palm trees and one dead oil palm tree were detected. No stressed oil palm trees were detected in the spatial subset image. In the ACSS2, there are 179 healthy oil palm trees out of 186. Three oil palms were detected in the slightly stressed category; however, no oil palm was detected in the S2 or S3 condition. Four oil palms were identified as dead in the image. In the ACSS3, there are 97 healthy trees and one dead oil palm tree. However, no stressed oil palms were detected in the S1, S2 or S3 condition. In the ACSS4, no healthy oil palm trees were identified. In addition, one oil palm is in the slightly stressed condition S1, five are in the moderately stressed condition S2, and one dead oil palm tree was detected. The ACSS5 indicates that only one dead oil palm tree was detected in the image. The ACSS6 reveals that there are 113 healthy, two slightly stressed S1 condition and seven dead oil palm trees in this image. However, no moderately stressed S2 and severely stressed S3 oil palm trees were detected. The qualitative analysis of ACSS7 reveals that there are 232 healthy, three slightly stressed S1 condition and nine dead oil palm trees in this image. However, there were no moderately stressed S2 or severely stressed S3 oil palm trees detected. Finally, the whole AISA classic image analyzed, there are 1125 healthy, 547 dead oil palms detected in the AISA Classic image. Furthermore, there were 598 oil palms in the slightly stressed S1 condition, 27 in the moderately stressed S2 condition and 19 in the severely stressed S3 condition found in the image.

Table 1. AISA Classic image spatial subsets qualitative analysis

ACSS	TA(ha)	TT	HT	ST			DT
				S1	S2	S3	
ACSS1	0.250	35	34	0	0	0	1
ACSS2	0.201	186	179	3	0	0	4
ACSS3	0.683	98	97	0	0	0	1
ACSS4	0.062	7	0	1	5	0	1
ACSS5	0.014	1	0	0	0	0	1
ACSS6	1.020	122	113	2	0	0	7
ACSS7	1.353	244	232	3	0	0	9
ACI	84.975	2286	1125	598	27	19	547

ACSSI =AISA Classic image subset, ACI= AISA Classic full image, TA = Total area in hectares, TT= Total number of trees, HT=Healthy trees, ST= Stressed trees, S1= Slightly stressed trees, S2= Moderately stressed trees, S3= severely stressed trees, DT=Dead trees

Table 2. AISA Eagle image spatial subsets qualitative analysis

AESSI	TA(ha)	TT	HT	ST			DT
				S1	S2	S3	
AESS1	1.000	173	139	20	12	0	2
AESS2	3.534	589	537	2	2	6	42
AESS3	0.040	1	0	1	0	0	0
AESS4	0.022	1	1	0	0	0	0
AESS5	0.250	30	29	1	0	0	0
AESS6	2.250	365	289	38	23	8	7
AESS7	1.020	140	137	2	0	1	0
AEI	36.371	5439	5287	69	38	45	288

AESSI =AISA Eagle image subset, AEI= AISA Eagle full image, TA = Total area in hectares, TT= Total number of trees, HT=Healthy trees, ST= Stressed trees, S1= slightly stressed trees, S2 = Moderately stressed trees, S3= severely stressed trees, DT=Dead trees

The AISA eagle image was resized into seven different spatial subsets (AESS) and the results analyzed for the validation of the algorithm. Finally, the whole AISA Eagle image was analyzed, the result depicted in Table 2. The AESS1 shows that there are 139 healthy, 20 slightly stressed S1 condition, 12 moderately stressed condition S2 and two dead oil palm trees in this image. No severely stressed S3 oil palm trees were detected. The AESS2 indicates that there are 537

healthy, two slightly stressed S1 condition, two moderately stressed S2, six severely stressed S3 and 42 dead oil palms. The AESS3 indicates that there is only one healthy oil palm in the image. Zero stressed or dead oil palm was found in the image. The AESS4 indicates that there is only one healthy oil palm in the image. No stressed or dead oil palm was found in the image. The AESS5 indicates that there are 29 healthy and one slightly stressed S1 oil palm in the image. No moderately stressed S2 severely stressed S3or dead oil palms were found in the image. The AESS6 indicates that 289 healthy, 38 slightly stressed S1, 23 moderately stressed S2, eight severely stressed S3 and seven dead oil palms were found in the image. AESS7 indicates that there is 140 healthy, two slightly stressed S1 and one severely stressed S3 oil palms. No moderately stressed S2 or dead oil palms were found. The whole AISA Eagle image shows that 5,287 healthy, 69 slightly stressed S1, 38 moderately stressed S2, 45 severely stressed S3 and 288 dead oil palms were found in the image.

4. CONCLUSIONS

The main notion behind the study was to propose an easily handled tool, for the qualitative analysis of hyperspectral data regarding individual oil palm trees, over the two study sites of Malaysia Lahad Datu and the Merilmau. Oil palm qualitative analysis is a laborious and complicated task; the proposed peak detection image processing algorithm solves this problem successfully. It is the simplest way to analyze individual oil palm trees by using image processing software ENVI and IDL. The results reported in CSV format were further analyzed using a data mining application in future.

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