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Application of Maximum Likelihood and Support Vector Machine: Determining Healthiness of Coconut Trees using SPOT6 Imagery

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ABSTRACT

Approximately 60% of the country's coconut plantations comprise various coconut species, which play a vital role in the national economy. However, infestations by the Red Palm Weevil (RPW) pose a significant threat, adversely affecting both the quality and yield of coconut production due to extensive damage to the trees. This study aims to detect RPW infestations in coconut plantations through the utilization of SPOT-6 satellite imagery, employing multiple classification techniques. Unsupervised classification methods were initially applied to derive the Normalized Difference Vegetation Index (NDVI) values, facilitating the differentiation of tree health status. Subsequently, supervised classification methods, namely Maximum Likelihood (ML) and Support Vector Machine (SVM), were implemented to evaluate their efficacy in identifying healthy and unhealthy coconut trees. NDVI values ranging from 0.33 to 1 were classified as indicative of healthy trees, whereas values below 0.33 were categorized as unhealthy. The results demonstrated that the SVM classifier outperformed the Maximum Likelihood approach, achieving an overall accuracy of 93% and a Kappa coefficient of 0.8543. These findings highlight the effectiveness of integrating GIS and remote sensing technologies in agricultural research and suggest significant potential for further development and commercialization of such approaches in precision agriculture.

Keywords: Driver; maximum likelihood; support vector machine; classification; red palm weevil; coconut trees; NDVI.

INTRODUCTION

Coconut plantations represent a major agroforestry resource and constitute one of the most economically important perennial crops in tropical regions, requiring continuous monitoring and effective management to sustain productivity and plantation health (Arumugam & Hatta 2022). However, plantation management faces numerous challenges, among which pest infestation is one of the most critical threats, particularly attacks by the Red Palm Weevil (RPW), Rhynchophorus ferrugineus (Murphy et al. 2021).

RPW is widely recognised as one of the most destructive pests affecting palm species and has caused severe damage to Cocos nucifera L. across tropical and subtropical regions. Over the past three decades, its rapid spread has been reported in several countries including India, China, Japan, Malaysia, the Philippines, and Vietnam (Fiaboe et al. 2012). Beyond coconut, RPW has also devastated date palm (Phoenix dactylifera L.) plantations in the Middle East, resulting in substantial economic losses and ecological consequences (Kang et al. 2022).

The high incidence of RPW outbreaks is strongly linked to delayed detection, improper disposal of infested trees, limited risk assessment practices, reduced effectiveness of natural predators, and low farmer participation in monitoring programmes (Kurdi et al. 2021). A major challenge in RPW management is the concealed nature of infestation. Early-stage attacks occur internally within the trunk, and external symptoms often appear only after severe structural damage has occurred (Ahmed 2020).

Visible indicators typically include frond discoloration, canopy wilting, and reduced vitality, but these symptoms emerge at advanced infestation stages (Bouthaina et al. 2024). Field inspection is further complicated by the height and structural complexity of coconut trees, making systematic ground-based detection difficult and labour-intensive (Massimo et al. 2018). Once severe symptoms such as crown collapse or internal trunk damage are detected, removal of the affected tree is often the only viable management option (Chandrashekar et al. 2020).

Given these constraints, the development of efficient early-stage detection methods is critically needed. Existing RPW detection approaches primarily fall into proximal sensing and field-based techniques. These include acoustic sensors that detect larval feeding sounds, thermal imaging to identify temperature anomalies, pheromone trapping, trunk injection diagnostics, and even trained sniffer dogs (Marzukhi et al. 2020; Massimo et al. 2018). While these methods can be effective at the individual tree level, they are operationally expensive, labour-intensive, and unsuitable for large-scale plantation monitoring. Consequently, they do not support systematic, landscape-level surveillance.

Remote sensing and Geographic Information Systems (GIS) have emerged as promising alternatives for detecting early vegetation stress prior to the manifestation of visible symptoms (Rakesh & Saket, 2020; Sishodia et al. 2020). Spectral vegetation indices derived from satellite imagery are sensitive to changes in chlorophyll content, canopy structure, and photosynthetic activity, which are often altered during biotic stress events. However, most previous remote sensing studies have focused on general vegetation stress, land cover classification, or disease detection in annual crops.

Medium-resolution imagery such as Landsat and Sentinel-2 has frequently been used, but its spatial resolution may be insufficient for detecting subtle crown-level stress in individual trees (Kassem et al. 2020; Sutanto et al. 2023). Conversely, UAV and airborne hyperspectral systems offer high spatial detail but are limited in coverage, cost efficiency, and operational scalability.

Importantly, satellite-based RPW detection in coconut plantations remains underexplored. There is a lack of studies evaluating whether commercially available medium–high resolution satellites can detect pest-induced stress at the plantation scale using operationally simple indices such as NDVI. Furthermore, limited research has examined the comparative performance of advanced machine learning classifiers against conventional parametric methods for this specific application.

Therefore, this study aims to detect RPW-related stress in coconut plantations using SPOT-6 multispectral imagery integrated with vegetation index analysis and supervised classification techniques.

By comparing Maximum Likelihood (ML) and Support Vector Machine (SVM) classifiers, this research evaluates the suitability of machine learning for discriminating healthy and unhealthy coconut crowns. The study contributes to the advancement of satellite-based pest stress detection by assessing the capability of medium–high resolution imagery to support early warning systems for perennial crop health monitoring.

METHODOLOGY

RESEARCH AREA

The study was carried out in a two-hectare coconut plantation located in Arau, Perlis, Malaysia, as illustrated in Figure 1. The plantation comprises 385 coconut trees, planted at a spacing of 27 feet by 27 feet. The geographic coordinates of the site extend from 6°27’35.84”N to 6°27’25.27”N latitude and 100°16’54.9”E to 100°16’54.8”E longitude. Field data were systematically collected through a census of each coconut tree using a handheld GPS device (GPSMAP®62sc, Garmin Ltd., KS model). This precise geolocation of individual trees facilitated accurate integration with satellite-derived vegetation indices, thereby enhancing the reliability and robustness of subsequent analyses.

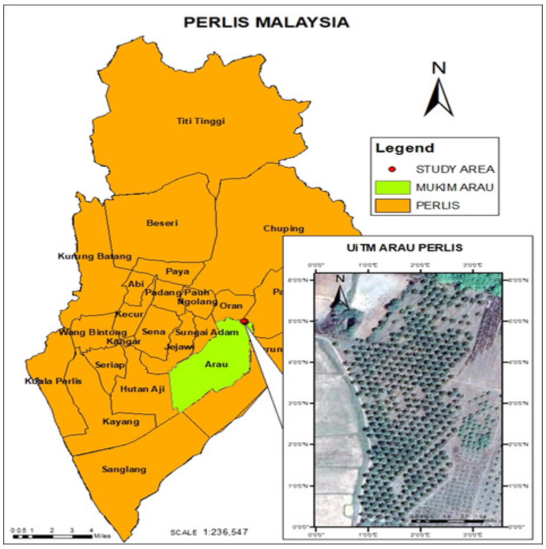

FIGURE 1. Research area

Besides, Figure 2 illustrates the methodology used in this study to identify the health of trees potentially affected by RPW. There are three main objectives to be achieved using field observation data, remote sensing data, and classification methods. At the end of the study, statistical analyses, namely confusion matrix and AUC/ROC were used to support the findings, as shown in Figure 2. The inclusion of multiple classification and validation approaches was intended to enable a more robust comparison of techniques and to ensure methodological rigor.

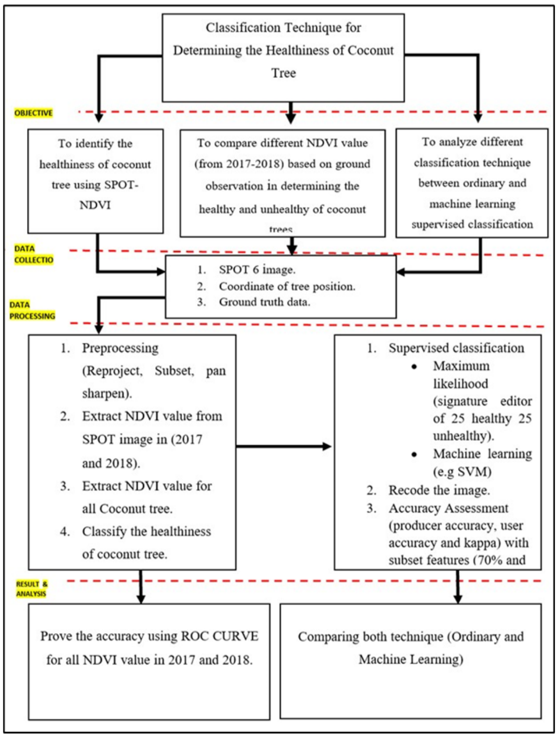

FIGURE 2. Methodology of work

FIELD OBSERVATION

A complete census-based ground survey was undertaken to generate a high-confidence reference dataset. The geographic coordinates of all 385 trees were recorded using a Garmin GPSMAP®62sc handheld receiver (±3 m positional accuracy). Each tree was assessed visually and classified into two health conditions: healthy (intact canopy structure, uniform green fronds, normal vigor) and unhealthy (frond discoloration, canopy thinning, wilting, or structural instability consistent with RPW-related stress). The use of full census data rather than sample plots minimizes sampling bias and ensures representativeness of class distributions. Ground-based classification serves as the empirical reference for supervised learning, enabling spectral signatures to be directly linked with observed physiological conditions. This integration of field and satellite data is critical for reducing classification uncertainty and for supporting quantitative validation.

REMOTE SENSING DATA

The research utilized SPOT 6 satellite images captured in both 2017 and 2018 to assess the health of coconut trees (Cocos nucifera). Various software packages, including ERDAS, ENVI, and ArcGIS, were employed to process the images and extract accurate data. The pre-processing steps included sub setting, geometric correction, image classification, and vegetation index extraction. A key component in this analysis was the Normalized Difference Vegetation Index (NDVI), a widely used indicator for assessing vegetation health.

SPOT 6 is an optical imaging satellite capable of providing Earth images at resolutions of 1.5 meters in panchromatic mode and 6 meters in multispectral mode (blue, green, red, and NIR spectral bands). It delivers imaging products to industries such as agriculture, forestry, environmental monitoring, and defense. The selection of SPOT 6 was selected due to its relatively high spatial resolution and inclusion of the NIR band, which are essential for detecting subtle stress signals in individual coconut trees and a critical requirement in early-stage RPW detection.

IMAGE PROCESSING

Pre-processing was conducted using ERDAS Imagine, ENVI, and ArcGIS to ensure spectral integrity and spatial accuracy. Radiometric correction was applied to reduce sensor-related and atmospheric variations that could introduce artificial spectral differences. Geometric correction was performed using 17 Ground Control Points

(GCPs), transforming imagery from WGS84 to Rectified Skew Orthomorphic (RSO) projection. The Root Mean Square Error (RMSE) was maintained below 0.5 pixels to ensure sub-pixel spatial alignment with field coordinates. Pan-sharpening was conducted using the Intensity-Hue-Saturation (IHS) fusion technique, integrating 6 m multispectral data with the 1.5 m panchromatic band.

This step improves spatial detail while preserving spectral relationships, which is particularly important for tree-level analysis in compact plantation layouts. The AOI was subsequently extracted to restrict processing to the study site, reducing computational noise from surrounding land covers.

VEGETATION INDEX EXTRACTION FROM SPOT6 IMAGERY

Vegetation indices utilize the red and NIR wavelengths to assess the greenness, health, and density of vegetation. In our investigation, we use the NDVI as an indicator in measuring coconut tree health since it is a simple and color-based measure employed frequently in remote sensing. NDVI is calculated by dividing the difference between the Near-Infrared (NIR) and red bands by their sum for each pixel in a satellite image. The resulting values range from –1 to +1. Healthy plants tend to exhibit higher NDVI values because they absorb more visible light and strongly reflect near-infrared light. Conversely, unhealthy or stressed vegetation reflects more visible light and less NIR light. However, it is important to note that vegetation indices such as NDVI do not account for atmospheric effects.

NDVI data can be used to estimate chlorophyll content, assess plant stress levels, monitor overall plant health, optimize fertilizer application, analyze plant diseases, and detect insect or pest infestations (Nik Effendi et al. 2024). In this study, remote sensing software was utilized to process the SPOT 6 satellite imagery and extract NDVI values. Several software options can be used for this purpose, including ENVI and eCognition.

However, Erdas Imagine 2014 was selected due to its familiarity and its efficiency in processing the specific dataset used in this research. Using this software, NDVI values were extracted with the NDVI tool available under the classification module, which uses the Red and NIR spectral bands to compute the NDVI value. This calculation follows the standard NDVI formula:

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

The equation explained above will always result in a NDVI plant health value between -1 and +1. According to Puteh et al. (2020), number between -1 and 0 suggests an inanimate or dead object, like roads, buildings, or dead plants. A NDVI plant health rating between 0 and 0.33 indicates unhealthy or stressed plant material, 0.33 to 1 is healthy tree (Debnath et al. 2021; Wesson & Britz, 2022). These numbers are just rules of thumb, and vary based on type of plant and other conditions. But that’s enough science for now.

Besides, this formula can be used to performing the calculation based on band manually. But, by using this Remote sensing software, it is more accurate and faster to generate all the NDVI value based on the pixel. The NDVI was process using NDVI tool under unsupervised tools that is indices tool. NDVI was selected as the primary vegetation index because it is sensitive to changes in chlorophyll content and canopy structure with two parameters strongly affected by early RPW infestation.

PIXEL-BASED CLASSIFICATION

To extract the NDVI values in this study, ERDAS Imagine and ArcGIS software were used. The Maximum Likelihood (ML) technique was applied for the first and second objectives of the study for pixel-based classification. Meanwhile, ENVI and ArcGIS software were used for the third objective, which involved supervised classification. The ML technique was used to classify the health status of coconut trees by comparing the results with ground truth data. This technique was employed to determine the most suitable classification method based on pixel-level analysis.

Two different pixel selection methods were applied to the SPOT 6 image: multiple-pixel selection and single-pixel selection. Multiple-pixel selection indicates that nine pixels surrounding each selected tree position were used, whereas single-pixel selection involves choosing only one pixel for each tree. This technique was implemented in the ML classification using the SPOT 6 satellite image acquired in November 2018. In this classification, two classes were considered as healthy trees and unhealthy trees with 25 Regions of Interest (ROI) selected for each class.

In addition, the Support Vector Machine (SVM) machine learning technique was used to classify the healthiness of coconut trees compared to the ground truth data. This technique was also employed to determine the best classification method using pixel-based analysis. Similar to ML, two-pixel selection methods which is multiple-pixel and single-pixel selection were used. For multiple-pixel selection, nine pixels around each tree position were used, while single-pixel selection used a single pixel per tree.

This approach was implemented in both ML and SVM classifications using the SPOT 6 satellite image from

November 2018. For both classification techniques, two classes were defined: healthy trees and unhealthy trees, with 25 ROI selected for each class. A total of 70% of the coconut tree samples (269 trees) were used for training, while the remaining 30% (116 trees) were used for testing. The subset feature tool in ArcGIS software was used to select the samples from the coconut tree dataset.

By using both ML and SVM allowed for performance comparison between a traditional parametric classifier and a more advanced non-parametric classifier, offering deeper insight into the most suitable classification technique for detecting RPW-induced stress. The pixel selection strategy was included to evaluate how spatial variability around each tree affects classification accuracy, thereby enhancing methodological robustness.

In addition, classification accuracy was evaluated using confusion matrix-derived metrics including Overall Accuracy (OA), Kappa coefficient, User's Accuracy, and Producer's Accuracy.

These metrics quantify classification reliability and omission/commission errors. Receiver Operating Characteristic (ROC) analysis and Area Under the Curve (AUC) values were further used to assess class separability independent of threshold effects. Combining these statistical measures ensures a comprehensive evaluation of model performance.

RESULTS AND DISCUSSION

IMAGE PROCESSING CLASSIFICATION

The SPOT-6 imagery acquired in 2018 was used to evaluate classification performance by comparing satellite-derived results with ground reference observations of healthy and unhealthy coconut trees. Both the original multispectral image and the pan-sharpened (IHS-fused) image were analysed. Image fusion enhanced the spatial resolution from 6 m to 1.6 m, allowing improved delineation of coconut crowns and reducing mixed-pixel effects commonly observed in medium-resolution satellite imagery. Improved spatial detail is particularly important in plantation environments where crown sizes are comparable to pixel dimensions, and spectral mixing can obscure stress signals.

The classification results demonstrate that pan-sharpened imagery significantly improved classification performance. The Maximum Likelihood (ML) classifier produced an Overall Accuracy (OA) of 88% and Kappa of 0.7533 for fused imagery, compared to 74% OA and 0.4080 Kappa for the non-fused image. This indicates that spatial resolution plays a critical role in distinguishing subtle spectral differences associated with vegetation stress. Similar improvements due to pan-sharpening have been reported in vegetation classification studies where enhanced spatial detail reduces within-class variability and improves class separability.

Compared to previous studies using Sentinel-2 imagery with ML classification reporting OA around 70% (Singh et al. 2019), the higher accuracy achieved here suggests that SPOT-6's finer spatial resolution provides improved sensitivity for crown-level discrimination. This highlights that, for perennial crops with discrete canopy structures, spatial resolution may be more influential than spectral richness alone. Table 1 shows the comparison for not performing image fusion and performing IHS for SPOT 6.

TABLE 1. Overall Accuracy for Not Performing Image Fusion and Performing IHS for SPOT 6

Multispectral Image	Overall Accuracy (%)	Overall Kappa
Not Performing Image fusion	74%	0.408
Performing (IHS) resolution merge	88%	0.753

DIFFERENTIATE THE HEALTHINESS AND UNHEALTHINESS OF COCONUT TREES BASE ON VEGETATION INDEX VALUE (NDVI)

Table 2 shows the total number of healthy and unhealthy of coconut trees in April 2017. 385 of coconut trees with different healthiness were found in this study area. The Maximum Likelihood method was used in this step to determine the NDVI value of the coconut tree. Based on the table 4.2, 1% of the 385 which is 3 coconut trees were classified as unhealthy tree because the NDVI value was less than 0.33, and 99% of the 385 which is 382 of coconut tree were classified as healthy tree because the NDVI value is more than 0.33.

In this study, Maximum likelihood classification technique was used to extract the NDVI value to assess the healthiness of coconut tree compared to ground data. An accuracy assessment was then necessary to validate the results by comparing the ground data with the extracted NDVI values. This threshold is supported by established NDVI standards indicating stress when values fall below 0.33.

TABLE 2. Total number of healthy and unhealthy of coconut tree in different years based on NDVI value.

Year	Healthiness	Total of trees	Percentage
Apr-17	Healthy	382	99%
	Unhealthy	3	1%
Oct-17	Healthy	385	100%
	Unhealthy	0	0%
May-18	Healthy	385	100%
	Unhealthy	0	0%
Nov-18	Healthy	352	91%
	Unhealthy	33	9%

As a result, a maximum likelihood classification allows the overall accuracy to be 92% and the kappa value to be 0.8649. The maximum likelihood classification for overall accuracy and kappa values in the previous study found at least 85% and the kappa value to be 0.71. The finding is presented better than Christobelle et al. (2016) where the overall accuracy is 92% and the kappa is 0.8649. The added comparison strengthens the statistical justification of the method. It is proved that the proposed method is significant to improve the healthiness of tree classification. In addition, the overall accuracy result is 7% more as compared to Christobelle et al. (2016).

In October 2017, there were 385 of coconut trees with different healthiness were found in this study area. The maximum likelohood method was also used to determine the NDVI value of the coconut tree. Based on the table 2, 0% which is no coconut tree were classified as unhealthy because the NDVI value was less than 0.33 is nothing, and 100% which is 385 of coconut tree was classified as healthy because the NDVI value is more than 0.33.

As a result, the coconut tree was in good condition in October 2017 because there was no NDVI value less than 0.33. In addition, according Inspection Officer of the Department of Agriculture (DoA) Perlis, there were no cases of pest infestation of Red Palm Weevil in the coconut tree in October 2017 in the coconut plantation area of UiTM Perlis. It can assume that the result was appropriate because it was compatible with the ground results.

In May 2018, 9% of 385 which is 33 coconut trees were classified as unhealthy tree because the NDVI value was less than 0.33, and 91% of the 385 which is 352 of coconut tree were classified as healthy because the NDVI value is more than 0.33. As a result, it can be inferred that the pest infestation is slowly starting to attack the coconut tree on that particular area based on the basis of the NDVI value. According to Walter-shea (2002), the NVDI value for unhealthy trees is less than 0.33 to -1, and the NDVI value that can be categorized as a healthy tree if more than 0.33 to +1.

However, in November 2018, 67% of 385 which is 258 coconut tree was classified as unhealthy because the NDVI value was less than 0.33, and 33% of 385 which is 127 of coconut tree were classified as healthy because the NDVI value is more than 0.33. According to Walter-shea (2002), the rate of NVDI value for unhealthy tree is below than 0.33 to -1, and the NDVI value that can be classify as healthy tree is more than 0.33 to +1. If the value less than -1 and more than 1, that can classify as others object. Figure 3 and Figure 4 shows the NDVI map of coconut trees healthiness in different years.

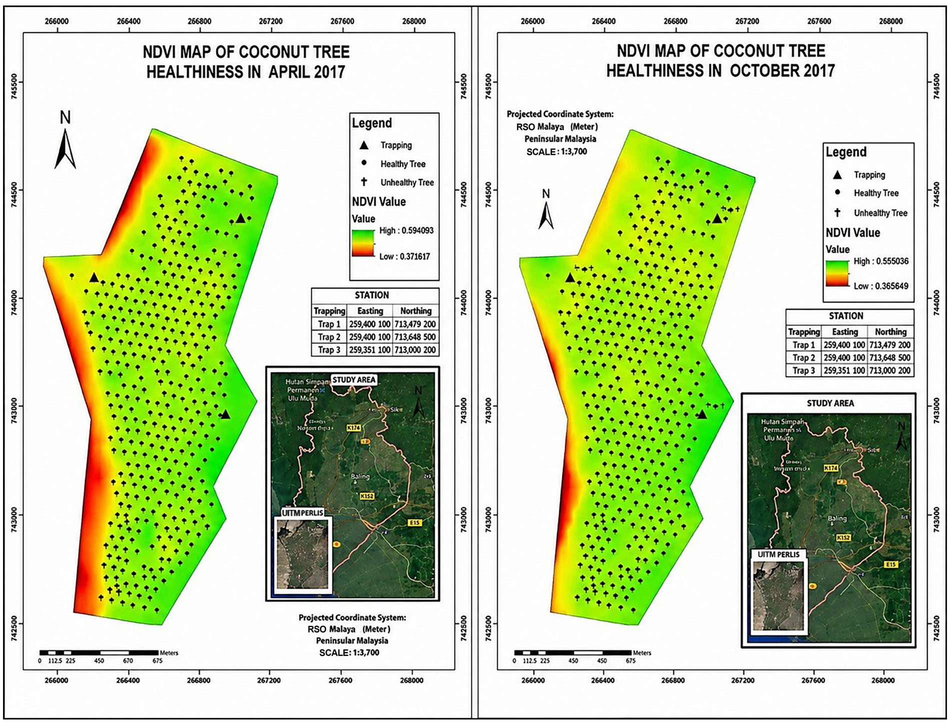

FIGURE 3. NDVI map of coconut trees healthiness in year 2017

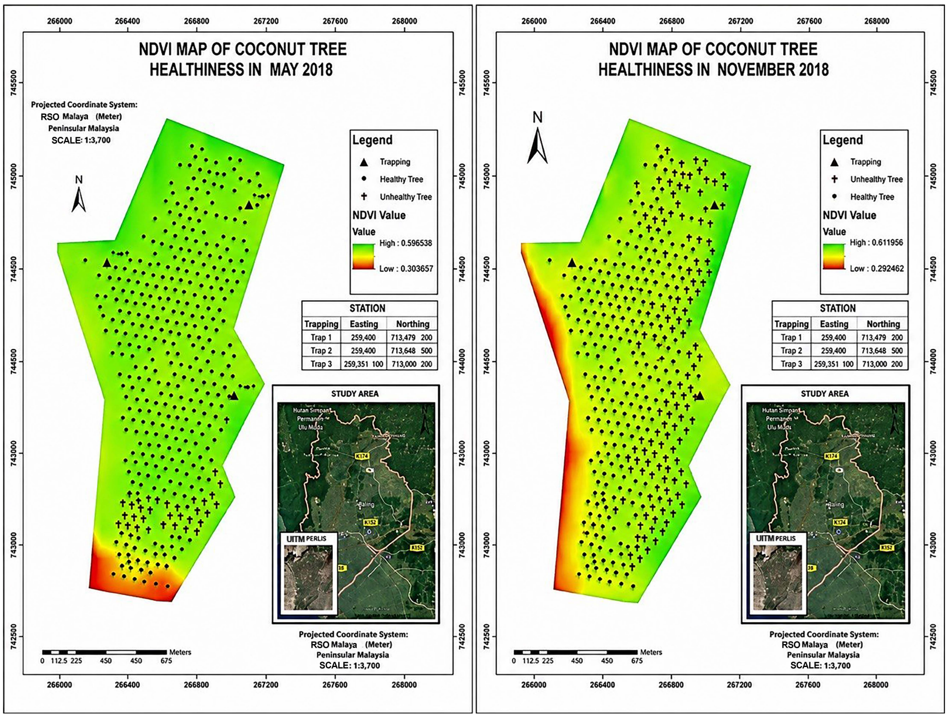

FIGURE 4. NDVI map of coconut trees healthiness in year 2018

STATISTICAL ANALYSIS FOR VALIDATION OF COCONUT TREE HEALTHINESS IN 2017 AND 2018

In Machine Learning, performance measurement is an essential task. When it comes to the classification problem, the Receiver Operation Curve (ROC) was used to test or imagine the output of the classification problem. It is one of the most important evaluation metrics for checking any classification model's performance It is also known as AUROC (The Receiver Operating Characteristics Area). Based on the Figure 5, it is shown that the ROC is performing to check the accuracy of classification. In this study, four SPOT6 satellite image were used in different month to classify the healthiness of coconut tree. In this section, the NDVI algorithm under the supervised classification method is used to evaluate the healthy and unhealthy of that coconut plantation. An expanded explanation is added to clarify how ROC evaluates separability between healthy and unhealthy classes.

When the NDVI value has been derived all trees, the accuracy assessment was performing to prove that particular value compared to the ground. The accuracy must be more than tolerance that is overall accuracy is more than 80% and the Kappa value is more than 0.6. After the accuracy assessment has been completed, ROC is used to prove the validity of NDVI and the classification process in all image.

Based on the Figure4, there are four different curves of different colors on the graph. A different curve was present the different image. The image used in this analysis is April 2017, October 2017, May 2018, and November 2018 which is consists of the NDVI value for healthy and unhealthy tree. As a result, the value of NDVI that obtained in April 2017, October 2017 and May 2018 based on table 3 was in the good result. This is because that AUC of three image is near to the 1 which means it has a good measure of separability.

A lower model is in May 2018 has AUC close and below 0.5, which means that it has a weak separability level. This is because when the AUC value is 0.5, it means that the model has no class separation capability whatsoever.

Nevertheless, this image can be considered not to be fairly acceptable. This is because the poor model has AUC close to 0 which means that it has the worst indicator of separability. As a result, this NDVI value can used to classify the healthiness of coconut tree which is if the NDVI value is less than 0.33 is the unhealthy tree and more than 0.33 is the healthy tree. The outcome of this analysis can be acknowledged. The statistical reasoning has been strengthened to ensure proper interpretation of AUC values.

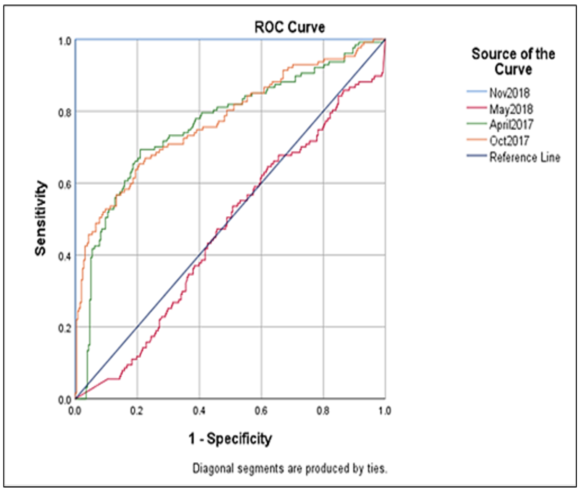

FIGURE 5. Roc curve of coconut tree healthiness in 2017 and 2018

COMPARISON OF ACCURACY ASSESSMENT FOR DIFFERENT ALGORITHM (ML&SVM)

Table 4 and 5 show that the comparison of overall accuracy and overall Kappa for two different classification techniques. To enhance scientific rigor, additional justification has been incorporated regarding why SVM outperforms ML in high-dimensional feature spaces. In this analysis, Maximum Likelihood (ML) as ordinary technique and Support vector machine (SVM) as Machine Learning technique was used to classify the healthiness of coconut tree compared to the ground truth data. Those two techniques are used to found the best classification technique by classifying on pixels.

Besides, in this pixel-based classification, two different methods have been selected for the pixel on the SPOT6 image which is selected by multiple pixels and single pixel. Multiple pixels selected indicates that the pixel was selected by nine-pixel numbers in one selected of the tree positions. For the single pixel selected mean, one-pixel number in one selected. This technique was implemented in the ML and SVM classifications using SPOT6 satellite image in November 2018.

Besides, in this classification, there are two types classes which is healthy tree and unhealthy tree with 25 ROI selected for each class. Based on table 4, there are two accuracy result which is overall accuracy and overall Kappa in two different techniques between ML and SVM. The accuracy was produced by compare the image classification to the ground truth data. The overall accuracy for ML in multiple pixels selected is 87.88% and the single pixel selected is 86.17%. For the overall Kappa in multiple selected is 0.7135 and the single pixel selected is 0.6685.

Besides, the accuracy for SVM is multiple pixels selected is 93.56% and for the single pixel selected is 88.66%. For the overall kappa in multiple pixels selected is 0.8543 and the single pixel selected is 0.7463. As a result, by using multiple selected technique is more accuracy compare to single selected technique. This result is also confirmed by two classification techniques that show the overall accuracy and overall Kappa of multiple pixels selected in higher than simple pixel selected.

In addition, it is shown that two different techniques have been used in supervised classification of ML and SVM. These different techniques are used to compared between ordinary with Machine Learning technique which one will get high accuracy in pixel-based classification. As a result, the accuracy of multiple pixel selected technique was used to make comparison between these ML and SVM. The overall accuracy of ordinary technique is 87.8873% and the overall Kappa is 0.7135. For the Machine Learning technique, the overall accuracy is 93.5573% and the overall Kappa is 0.8543.

As a result, the value of accuracy by using SVM is higher value which is the overall accuracy is 5.67% and overall Kappa value is 0.1408 more than ML. It can be inferred that SVM (Machine Learning) classification technique is the better classification method compared to the ML (Ordinary) technique. These results demonstrate that SVM provides better class separability, likely due to its ability to map nonlinear boundaries in pixel-based classification.

TABLE 3. Area under the curve (AUC)

Area Under the Curve					
				Asymptotic 95% Confidence interval	
Test Result Variable(s)	Area	Std. Error	Asymptotic Sig.[b]	Lower Bound	Upper Bound
Nov2018	1.000	0.000	0.000	1.000	1.000
May2018	0.468	0.031	0.307	0.407	0.529
April2017	0.762	0.028	0.000	0.708	0.816
Oct2017	0.773	0.027	08.000	0.720	0.826

TABLE 4. Comparison of overall accuracy and overall kappa between maximum likelihood and Support vector machine.

	Maximum likelihood (ML)		Support vector machine (SVM)	
Sample Design	Multiple Pixel (3x3)	Single Pixel (1x1)	Multiple Pixel (3x3)	Single Pixel (1x1)
Overall Accuracy	87.88%	86.17%	93.56%	88.66%
Overall Kappa	0.7135	0.6685	0.8543	0.7463

TABLE 5. Comparison of user and producer accuracy between maximum likelihood and Support vector machine

	Maximum likelihood (ML)		Support vector machine (SVM)		
	Healthy	Unhealthy	Healthy	Unhealthy	
User Accuracy	84.31%	89.33%	84.17%	98.65%	Multiple Pixel (3x3)
Producer Accuracy	76.11%	93.39%	97.12%	92.02%	
User Accuracy	81.05%	88.16%	75.45%	96.32%	Single Pixel (1x1)
Producer Accuracy	72.64%	92.31%	92.22%	87.14%	

COMMISSION AND OMISSION ERROR FOR NOVEMBER 2018

Classification performance was evaluated using a confusion matrix, which provides a quantitative comparison between classified outputs and ground reference data. Overall Accuracy (OA) represents the proportion of correctly classified samples relative to the total number of reference samples and is expressed as a percentage. It is calculated by summing the diagonal elements of the confusion matrix, representing correctly classified instances and dividing by the total number of samples. While OA offers a general indication of classification performance, it does not capture class-specific reliability or the nature of classification errors.

To provide a more detailed assessment, omission and commission errors were analysed for each class. Omission error refers to reference samples that were incorrectly excluded from their true class in the classified map, indicating under-representation of that class. This error is computed by examining the column totals of the confusion matrix and dividing the number of incorrectly classified reference samples by the total number of reference samples for that class. Conversely, commission error represents samples that were incorrectly assigned to a given class, indicating over-representation. This is derived by evaluating row totals and dividing the number of misclassified samples by the total number of samples classified into that class. An omission error in one class inherently contributes to a commission error in another, reflecting the interdependent nature of classification inaccuracies.

Producer's Accuracy (PA) and User's Accuracy (UA) were further used to quantify class-specific performance. Producer's Accuracy measures the probability that a reference sample of a given class is correctly classified and is therefore related to omission error (PA =1−omission error). It reflects the perspective of the map producer, indicating how well real-world features are represented in the classification. In contrast, User's Accuracy expresses the likelihood that a sample labelled as a given class on the map truly represents that class on the ground (UA = 1 − commission error). UA thus reflects map reliability from the user's perspective.

The combined use of OA, PA, UA, and class-specific error rates provides a comprehensive evaluation framework, allowing both global and class-level interpretation of classification performance. This multi-metric approach ensures that the confusion matrix is not merely presented descriptively but is directly linked to the overall reliability and usability of the classification results as shows in Figure 6.

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Confusion Matrix: Support Vector Machine (6x6) November 2018

Overall Accuracy = (320/342)  93.5673%
Kappa Coefficient = 0.8543

                 Ground Truth (Pixels)
   Class     EVF:UnhealthyEVF:Healthy_t        Total
 Unclassified             0            0           0
    Unhealthy           219            3         222
      Healthy            19          101         120
        Total           238          104         342


                Ground Truth (Percent)
   Class     EVF:UnhealthyEVF:Healthy_t        Total
 Unclassified          0.00         0.00        0.00
    Unhealthy         92.02         2.88       64.91
      Healthy          7.98        97.12       35.09
        Total        100.00       100.00      100.00


        Class   Commission     Omission        Commission          Omission
                 (Percent)    (Percent)          (Pixels)          (Pixels)
    Unhealthy         1.35         7.98             3/222            19/238
      Healthy        15.83         2.88            19/120             3/104

        Class   Prod. Acc.    User Acc.        Prod. Acc.         User Acc.
                 (Percent)    (Percent)          (Pixels)          (Pixels)
    Unhealthy        92.02        98.65           219/238           219/222
      Healthy        97.12        84.17           101/104           101/120
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FIGURE 6. Confusion matrix

CONCLUSION & RECOMMENDATION

This study demonstrates that SPOT-6 multispectral imagery, when integrated with NDVI and supervised machine-learning classification, provides a scientifically robust framework for detecting physiological stress in coconut trees associated with early Red Palm Weevil (RPW) infestation. The results confirm that spectral vegetation indices derived from medium to high spatial resolution imagery are sufficiently sensitive to capture canopy reflectance variations linked to pest-induced stress, even before severe visual symptoms become apparent.

A key analytical finding of this research lies in the comparative performance of classification algorithms. The consistent superiority of the Support Vector Machine (SVM) over the parametric Maximum Likelihood (ML) classifier highlights the importance of non-linear decision boundaries in discriminating subtle spectral differences between healthy and unhealthy coconut crowns. This suggests that RPW-induced stress manifests as complex spectral responses rather than normally distributed class signatures, thereby justifying the use of machine-learning approaches for plantation health monitoring.

Methodologically, this study contributes to the remote sensing literature by operationalizing an NDVI threshold (0.33) for coconut health assessment under tropical plantation conditions and validating it using ground census data, confusion matrices, and ROC–AUC analysis. The integration of multi-temporal imagery further strengthens the analytical framework by demonstrating how vegetation indices can capture temporal stress progression, linking spectral decline patterns to potential pest outbreak dynamics. This temporal-spectral coupling represents an advancement beyond static classification approaches commonly reported in plantation monitoring studies.

From a broader scientific perspective, the research bridges a gap between agricultural pest management and satellite-based vegetation health modelling. While previous RPW detection methods rely heavily on field inspection, acoustic sensing, or UAV-based approaches, this study establishes that commercially available satellite data can support scalable, landscape-level early warning systems. The findings therefore extend the application domain of medium-resolution remote sensing from general land-cover mapping to precision pest-stress detection in perennial crops.

Practically, the framework offers a cost-effective monitoring strategy for agricultural agencies and plantation managers by enabling rapid identification of stress hotspots requiring field verification. This supports proactive intervention rather than reactive tree removal, contributing to sustainable plantation management and food security.

Future research should incorporate very-high-resolution imagery, hyperspectral sensors, LiDAR integration, and deep learning models to improve crown-level discrimination and to separate RPW stress from other abiotic or biotic stress factors. Such advancements would enhance species-specific stress diagnostics and strengthen operational early detection systems

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DECLARATION OF COMPETING INTEREST

None.

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