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MAPPING MANGROVE DENSITY FOR CONSERVATION OF THE RAMSAR SITE IN PENINSULAR MALAYSIA

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Abstract

It is widely agreed that rapid development has led to mangroves being in urgent need of improved monitoring and assessment techniques for better conservation. In Malaysia, the Convention on Wetlands, otherwise known as the Ramsar Convention, came into being specifically to address this problem and protect this particular area. The rapidly rising sea-level at mangrove sites is currently impacting the depth of mangrove soil, so action must be extended using available technology to sustain mangrove lives. This study tested if the vegetation indices from recent high-resolution multispectral satellite images Satellite Pour l'Observation de la Terre, known as SPOT, can map mangrove density and predict health area for the sites. An Unmanned Aerial Vehicle (UAV) was also used to fly at the nearer sites for mangrove density classification mapping based on feature extraction tools classification. This study employed Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Greenness Vegetation Index (GVI), and Ratio Vegetation Index (RVI) to map mangrove density for the study site. The study showed, in terms of Maximum Likelihood Classifier (MLC) measurement, that 52% of the area was "high density", 10%-19% was "low density", and "low density mixed sand" and also "sand" area. The results also showed that NDVI responded higher for "high density" with 0.56, GNDVI with 0.27 for "high density", GDVI with 17.0, and RVI only classified two density areas. In addition, the UAV images were classified into shadow, obvious tree crown, vegetation in the water, sea area, and others. As expected, the study revealed that UAV (b) was presented in a very high percentage in obvious tree crowns but in a low percentage with 2% of other classes, making it a distinct class from others. In addition, UAV (a) showed 42% shadow with a small portion distributed in other vegetation features (sea area and others) class, 4% to 10%. Mangrove density can also be used as an indicator of mangrove health status because low density mangroves are always found near to the risk areas.

***Keywords**: Mangrove; Peninsular Malaysia; Vegetation indices*

Introduction

Mangroves are important for global land sustainability and Malaysia. Any disturbance affecting mangroves, including land conversion from the construction of aquaculture projects, can diminish the mangrove forests. Reports from the Food and Agriculture Organization of the United Nations (FAO) found that mangrove areas had decreased from 16.1 million hectares (1990) to 15.6 million hectares (2010) [1]. In fact, it was found that mangrove forests had faced numerous problems, including land degradation, species depletion, and shifting cultivation which has exposed such forests to long-term threat. Peninsular Malaysia boasts several mangrove forests: Tumpat, which is located in Delta Kelantan; Matang Mangrove Forest Reserve in Perak; mangrove forests in Tanjung Tuan Port Dickson and Negeri Sembilan; and

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Sungai Pulai Forest Reserve, which is located in the southern part of Peninsular Malaysia near to Tanjung Piai, the study area for this research. The significance of the role of mangroves for the Malsian peninsular has been addressed by many researchers through their findings; for example, in a recent study of the diversity of mangrove plants in Sibuti mangrove forest, Sarawak [2]. Indeed, it can be said that research stressing the importance of the role of mangrove forests on the peninsular has been ongoing. One study, for example, assessed the composition and diversity of mangrove stands in Sibuti mangrove forest in Sarawak [2]. Other studies have explored the application of Geographical Information System (GIS) and remote sensing for monitoring the forests; for example, in 2007 [3] researchers evaluated Kuala Selangor mangroves based on GIS and remote sensing techniques. A more recent and detailed study was conducted in 2015 and became [4] the satellite monitoring study for the whole mangrove population of peninsular Malaysia. Other recent research has focused on remote sensing, applying the WorldView satellite for estimating mangrove biophysical variables [5], [6] and for mapping and the identification of mangrove species [7].

Wetlands are among the world's most protected environments [8]. Ramsar: The Convention of Wetlands was developed in Iran for this purpose and began in 1971. Many studies have been conducted to monitor wetlands, with particular interest in mangrove forests. One study [9] conducted an assessment of the rejuvenation rates of mangroves in Matang Mangrove Forest Reserve for conservation purposes, based on mangrove density for all species. Rapid land cover changes have enabled satellite remote sensing techniques to be more efficiently applied. As a result, from 2012 studies grew which applied remote sensing for research. [10] The WorldView-2 satellite was employed, for example, for estimating high density wetland biomass in KwaZulu-Natal Province, South Africa. A more recent study in 2017 [11] employed the 8-m GF-1 Chinese series high resolution satellite with four multispectral bands from 450 nm to 890 nm. The advantages afforded by higher resolution images have continued to be enjoyed by other research projects. For example, in Sungai Pulai, Tanjung Piai and also in Pulau Kukup, Johor research has been conducted based on SPOT-5 and other low resolution satellites such as Landsat-7 ETM and Landsat-8 OLI [12].

Human activity has, of course, modified the forests and the effects are now predicted analytically by indices; for example, by mathematical combination of spectral channels. This combination method has been used as a medium for analysing changes via the application of vegetation indices, although this does not discriminate well between vegetation communities [13], measured according to the normalized difference vegetation index (NDVI). The utilization of NDVI has been effective for tropical areas such as the sub-tropical mangroves of South East Queensland, Australia [14]. NDVI is highly associated with biomass, providing it is applied at wetland biomass areas involving the new-red edge band from satellite WorldView-2 [10]. In the meantime, the green normalized difference index (GNDVI) has been applied to assess biophysical variation of mangroves [5] and was also noticed in water indices application and known as other indices for estimation of leaf area index [16]. GNDVI was also applied for quantifying analysis between the remotely-sensed data of WordView and mangrove chlorophyll content [17]. It is widely-seen that, given this background there is an urgent need for incorporating vegetation indices in order to assess the health of mangrove areas. The objective of the present study was to map mangrove density based on vegetation indices from SPOT-6 satellite images for health area identification.

Methodology

Study area

The chosen study area was the mangrove forest of the Tanjung Piai Forest Reserve located at Pontian, Johor, Malaysian Peninsula, Malaysia. Bordering the study area is an established palm oil plantation. The wider area is known as the Southernmost Tip of Mainland

Asia, and it is also strategically located at the confluence of the Malacca Straits, the Singapore Straits, and the Johor Straits.

Historically, Tanjung Piai is named after a local fern, known as the "Paku Piai" which is capable of living in brackish conditions. The park covers 526 hectare of mangroves and another 400 hectares of inter-tidal mudflats. The area is characterized by mudflat mangroves, which live with rich flora and fauna. The area is, in fact, home to about 20 'true' mangrove species, 9 related mangrove species, 3 types of primates, one endangered bird called the Lesser Adjutant Stork (*Leptoptilus Javanicus*), mangrove crabs, and mudskippers [18]. Tanjung Piai is considered pristine land and is managed by Johor National Parks. It was also registered by ***Ramsar*** Convention on Wetlands of International Importance as Ramsar Site no. 1289 in 31 January 2003. The area is utilized by villagers and is their main source of income in the form of fishing activities and the extraction of other forest resources such as coal. The area was selected as the study site because Tanjung Piai is currently threatened by the development of a mega project of an approximately 3,485 acres of land which will be reclaimed off the coast of Tanjung Piai. Tanjung Piai Maritime Park will form a man-made island to be sited off the south-western coast of Johor, as declared in a statement at www.tgpiaimaritime.com.my [19]. In addition, Tanjung Piai is surrounding by a palm oil plantation. One consequence is that the area experienced drastic land use changes between 1989 to 2014 because of oil palms and rubber plantations, and general urbanization. Figure 1 illustrates the location of Tanjung Piai based on MODIS satellite image for Malay Peninsula and SPOT-6 for the study area.

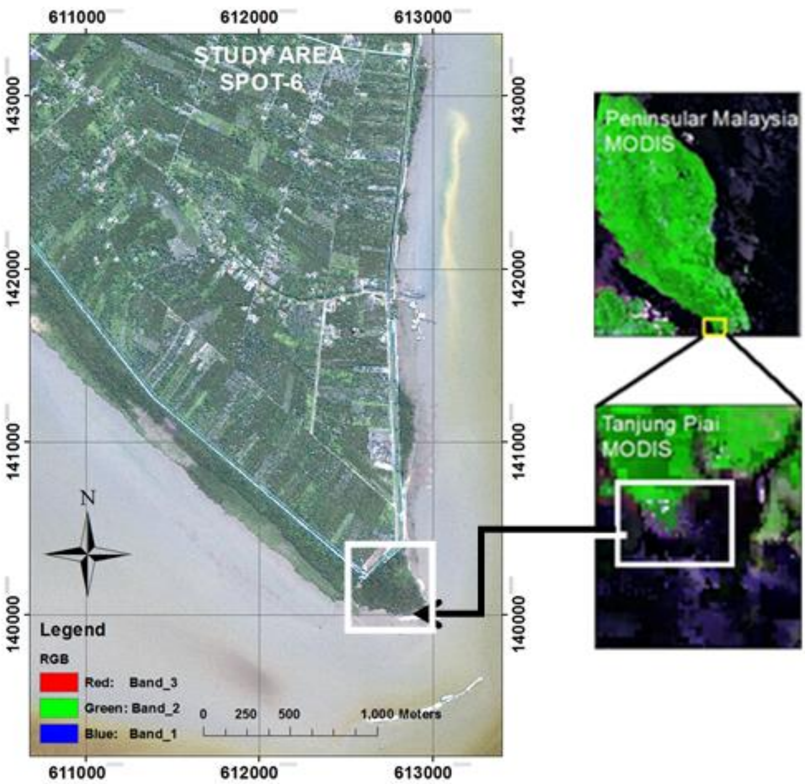

Fig. 1. The location of Peninsular Malaysia (MODIS satellite image), Tanjung Piai (MODIS satellite image), and SPOT-6 dated 2015 (the study area), showing the study area with 3, 2, and 1 band combinations for natural colour

Satellite data

In the present study, a SPOT-6 with a 1.5-m multispectral resolution band was purchased from the Malaysian Remote Sensing Agency (ARSM). The image dated 11th May 2015 was chosen because the scene was categorized as minimal cloud. The satellite was built by AIRBUS Defence and Space, which was successfully launched on 9th September 2012. In this activity, the ground routes were divided into Route 1 and Route 2, which consisted of two different ground check routes. The first route was comprised of points 6, 1, 3, 4, 7, and 5, and the second route was comprised of points 6, 1, 3, 4, 7, 2, and 5. SPOT resolution showed its capability in its classification of land covers performed by a study of [20] based on SPOT-VGT data. The images were first analysed for cloud detection based on [21], which assumes that clouds are connected objects, that solar/sensor geometry is known, and that shadow has a similar shape to its corresponding cloud (excluding the influence of topography). The image identified no potential pixels of cloud and shadow, therefore no specific cloud removal was conducted for the image.

NDVI is a measure between the red and the near-infrared (NIR) spectrum which enables measures changes in visible red radiation in satellite images and in spongy mesophyll via reflected radiation within the vegetation canopy [22]. NDVI for example, is sensitive to chlorophyll and photosynthetic vegetation as cited in a study [23]. This index was selected because it is known to be very good for the detection of biomass reduction in tropical forests as a consequence of abiotic stress, particularly suitable for the Tanjung Piai area. The NDVI is more suitable for use in the tropics compared with the Arctic because in the Arctic plant density is low and snow melt creates areas of standing water. Such areas are also affected by soil reflectance in sparsely vegetated areas, leading to underestimations of biomass [24]. The indices have a scaling format of −1 to +1, a scaling which was developed in a previous study [25]. Vegetation areas are indicated as a value of more than zero, whereas water and non-vegetated land is represented by negative values. The equation for the NDVI calculation is given as:

$$NDVI = NIR - Red/NIR + Red \tag{1}$$

GNDVI is a modification of NDVI in which red bands are substituted with the reflectance in Green bands. The index was developed by [26] and is more sensitive to denser canopies [27]. This index is added to this study because NDVI may not be sufficiently sensitive to foliage variation to allow for quantitative monitoring of canopy drought stress [28]. The index is expressed as follows:

$$GNDVI = NIR - Green/NIR + Green \tag{2}$$

GVI is an index based on the calculation for Near-infrared and green bands, with no ratio calculation involved. The index is expressed as follows:

$$GDVI = NIR - Green \tag{3}$$

RVI is an index for estimating the green portion in images and was developed by [29]. The index was also listed by [30] as a simple ratio vegetation index (SVI), which is counted based on Near-infrared and red bands. This index was also applied in a study which was related to land surface temperature [31]. The index is useful for supporting the NDVI index, because it also eliminates the effects of changing the level of illumination because if the sunlight intensity doubles then both red and NIR measures will also be double. The index is estimated as:

$$RVI = NIR/Red \tag{4}$$

Note: NIR = Near-infrared

Classification of mangrove density

In this study, the mangrove density classification percentage was calculated based on the MLC. The MLC was selected because it can be used to estimate the posterior probabilities of different land cover types. Furthermore, a standard MLC is typically used for its high computing efficiency and acceptable accuracy [32]. MLC is a pixel-based approach measuring spectral data derived from pixel cells. The classifier is conducted based on ENVI 8.0 software which, in this study, was integrated with information gathered from the field visits. The general formula is described below:

$$\text{Mangrove density MLC} = \text{Area in Class/Total test site} \quad (5)$$

The density was counted based on zonal histogram tools. For calibration, an Unmanned Aerial Vehicle (UAV) data flight was planned to the areas on October 2017. Four scenes were collected based on easy access to the areas. The images were segmented based on feature extraction analysis from spatial analyst tools in ArcGIS 10.3. We chose segmentation because this technique is very suitable because of concerns for image resolution: UAV raster format can be easily converted into polygon for raster data classification.

Results and discussions

MLC density mapping

Mangrove density mapping can represent an overview of the health of the mangrove forest. Based on MLC, four classes of density were categorized and identified on SPOT-6. As can be seen from Table 1, the mangrove density was identified into "low density", "high density", "low density mixed sand," and "sand". The low density area was classified as mixed with sand features (Fig. 2). The density classification gave results of "low density" concentrated in the "high density" mangrove forest with an area of 19%. "Low density mixed sand" was located at the edge of the forest with area of 19% or around 2.14 ha. The level of density which clearly dominated the area was "high density," making up 52% of the area or 5.82 ha. Area for all density classes ranged from 10% to 52%, indicating a moderate area percentage for all of the classes.

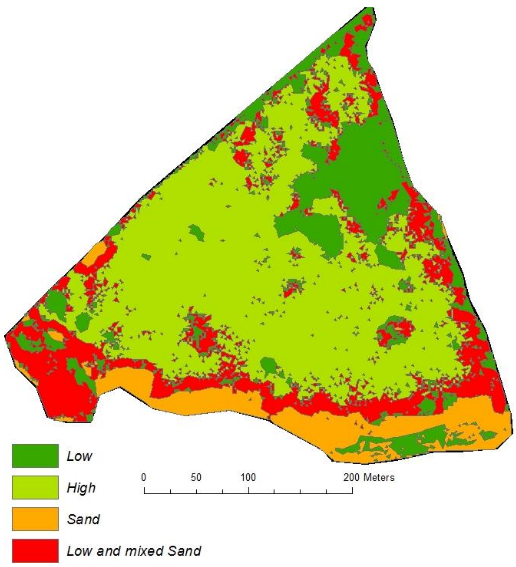

Fig. 2. MLC density classification for mangroves at Tanjung Piai

Table 1. Areas of MLC classification for Tanjung Piai

MLC class	Pixel count	Area (m^2)	Area (ha)	Area (%)
High density	17961.00	58193.64	5.82	52
Low density	6373.00	20648.52	2.06	19
Low density mixed sand	6609.00	21413.16	2.14	19
Sand	3310.00	10724.40	1.07	10
Total	34253.00	110979.72	11.10	100

This mangrove area is managed by Johor National Park, which means that tree development is always monitored by their management team. The area is monitored daily for routine purposes and involves flood monitoring and safe-guarding from outsiders and non-registered visitors such as campers or villagers who may cause damage to the parks and tree development. Such routine monitoring activities might be the reason for the study site having such a dominant level of "high density" mangrove percentage, while also being due to natural stands having a higher spatiotemporal heterogeneity development and succession [33] as found in mangrove forest studies in China.

UAV density mapping

This study found that shadow covered 42% of UAV(a), and at the same time presented the second highest obvious tree cover in comparison with other scenes with a 30% of UAV. High shadow represents a high number of tree life and standing, which can be classified as "high density" area as presented in MLC classification (Fig. 3).

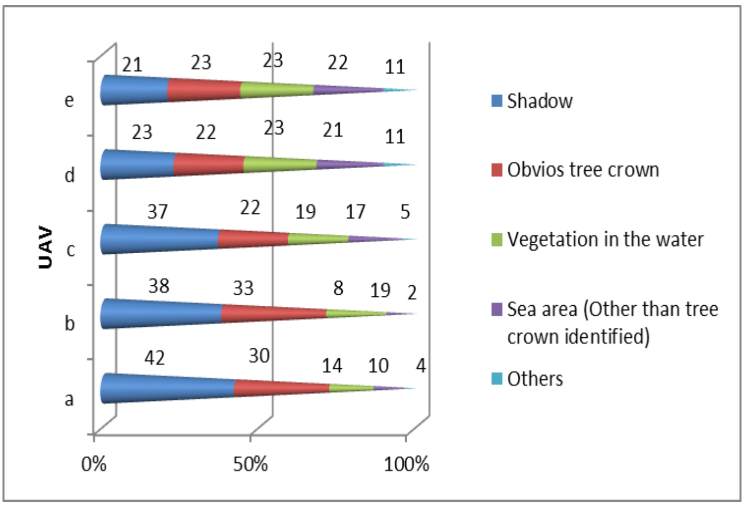

Fig 3. Feature extraction for the UAV images at calibration sites

UAV(b) and UAV(c) showed shadow around 37%-38% while others showed below 25%. UAV(d) and UAV(e) showed a similar percentage of other classes with 11%. The feature extraction tools showed that UAV(a) was comparable with UAV(c); and UAV(d) was comparable with UAV(e). As expected, the results showed that UAV(b) was present in a very high percentage in the tree crowns but in a low percentage at 2% of others classes, making it a distinct class from others. For calibration, five UAV images were collected (Fig. 4a to d). After carrying out the segmentation process, the features were identified as shadow, obvious tree crown, vegetation in the water, sea area, and others. The images showed a different tree distribution with trees in the water, therefore being exposed more to the sea waves, with the edge of some areas facing the sea. UAV(e) was a mangrove with the largest distance from the sea, compared to UAV(b) and UAV(d). In fact, UAV(e) stands directly in the water: it was observed that this made the trees grow less and increased the likelihood of the trees becoming susceptible to poor health and exposure to risk from pests and diseases. UAV(c) and UAV(a) were at a similar distance from the sea, meaning that the forest area is located away from the seas, creating more opportunity for the trees for prolonged standing, which led to the development of healthier growth mechanisms. From ecologists' findings, it is predicted that some trees will out-perform others and this difference in performance creates crowding and increased forest density. Results showed that UAV has a high level of capability for being utilized as a mapping tool for forested areas. Indeed, UAV is mostly used for plantations production monitoring, mainly for palm oil plantations. In fact, due to its extra resolution, the images show many pixels mixed with leaves and backgrounds, e.g., the pixels located on the edge of a canopy or the crown gaps [34]. Therefore, this spatial feature extraction tool is very useful for the researcher.

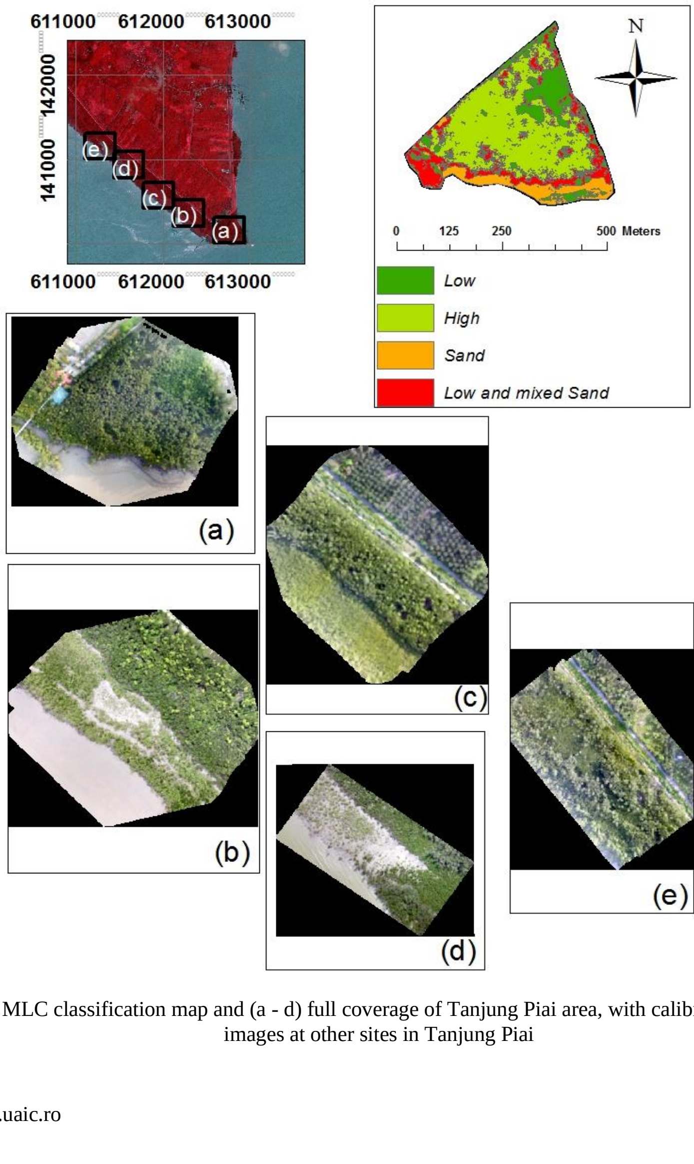

Fig. 4. MLC classification map and (a - d) full coverage of Tanjung Piai area, with calibration of UAV images at other sites in Tanjung Piai

Vegetation indices density mapping

The vegetation indices map is classified into four density classifications based on the Natural Breaks classifier in ArcGIS, with except RVI produced with two classes. The density map shown in Figure 5, was RVI which showed the lowest density class, indicating insufficiency employment of band numbers in the equation. Although RVI was not able to delineate between low and high density, it was managed to identify sand out of the vegetation area, particularly at the edge of the forest. In this study, an accumulated index produced four density classes, dominated by a lower density area. Other classes were delineated by classification as GNDVI.

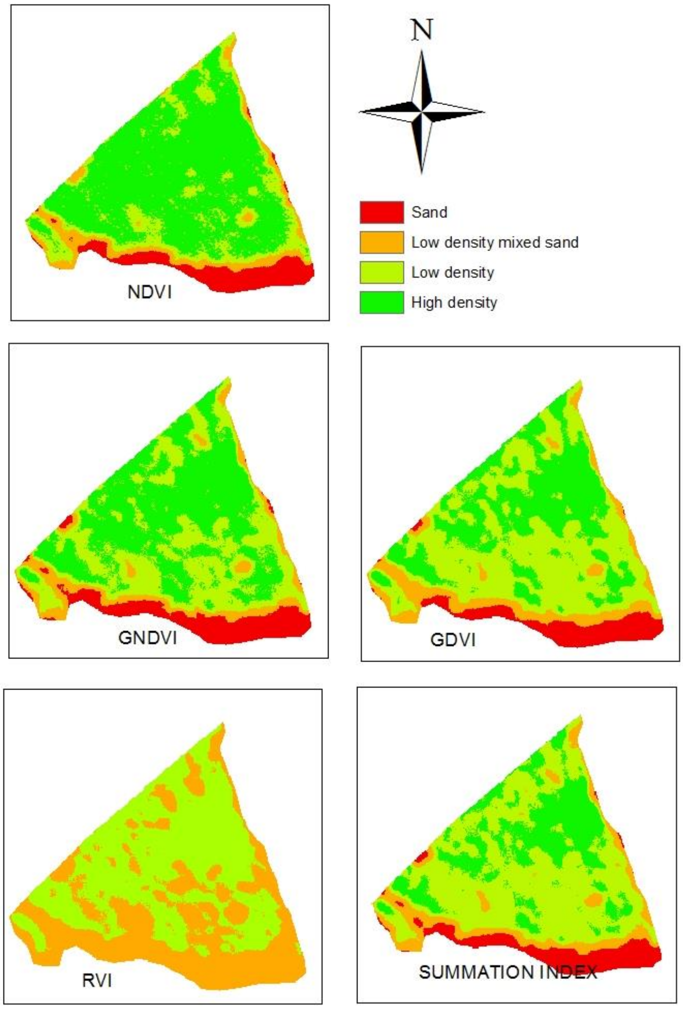

Fig. 5. Vegetation indices density map

High density is represented by a NDVI value of more than 0.50, with GNDVI was 0.27. GDVI showed 22.0 which have different value scale than NDVI. This is because GDVI give an estimate of the green portion in the equation without applying a ratio function. RVI, however, with the function of rationing near infrared and red bands produced two classes only. Low index was shown for “Low density mixed sand”, illustrating that the presence of mangrove wetness affects the vegetation index value, particularly for NDVI.

NDVI results were concurrent with MLC classification, which showed a “High density” for higher NDVI values, also agreeing with GDVI “High density”. The results were also consistent with “Low density” and “Low density mixed sand” with low index value. A study conducted in Maubes Nature Reserve found NDVI values above the threshold (0.3 in this study) being identified as vegetated areas, while low NDVI values represented non-vegetated areas [35].

Table 2. MLC classification for Tanjung Piai

Index	Index value			Area (%)
	MIN	MAX	STD	
NDVI				
Low density	-0.22	0.56	0.17	19.2
Sand	0.23	0.50	0.03	9.7
Low density mixed sand	-0.43	0.15	0.07	8.7
High density	-0.38	0.56	0.09	62.4
GNDVI				
Low density	-0.22	0.28	0.12	10.0
Sand	0.08	0.22	0.02	19.3
Low density mixed sand	-0.45	-0.06	0.05	18.7
High density	-0.45	0.27	0.08	52.1
GDVI				
Low density	-20.00	22.00	9.63	10.0
Sand	4.00	13.00	1.62	19.3
Low density mixed sand	-21.00	-3.00	3.67	18.7
High density	-15.00	17.00	4.66	52.1
RVI				
High density	0.00	1.00	0.48	54.4
Low density	0.00	1.00	0.46	45.6
Accumulated index				
Low density		-		10.5
Sand		-		12.0
Low density mixed sand		-		51.9
High density		-		25.6

SPOT-6 was employed for mapping due to its capability for differentiating between vegetation and non-vegetation areas. The percentage of the area covered by each of the MLC classes showed that SPOT-6 had a superior potential for mangrove area mapping; particularly for high and low mangrove densities. More recently, SPOT satellite imaging has become very popular as a tool for efficiently mapping vegetation, particularly SPOT-VGT. This method has, in fact, become the chosen method for updating via the user community and for governments in terms of their environmental policy-making [36] and SPOT has been recently widely employed for various studies related to landscape mapping [6, 24, 37]. With such a reliable method of obtaining satellite images, this study tested this method for mapping mangrove density in the important Ramsar area in the peninsula. The density mapping was calibrated with UAV. The UAV revealed a huge potential for density mapping if the tree structures were to remain in this form for some time without a large catastrophic change from the sea or land. As discussed in a previous study [37], terrestrial vegetation plays a huge role in land-atmosphere interaction. Therefore, this study advises that this application should be continually carried out because it is based on reliable satellite images of the high risk and important areas discussed.

Naturally, the results illustrate that the UAV(b) presented a distinct class from others, with more obvious tree crowns identified. This makes the area healthier for tree growth compared to UAV(e) with stands in the water, which may result in susceptibility to poor health and more prone to attack from pests and disease. Also, with the performance features of

UAV(e) it was found that this could be followed by low NDVI values if the index was tested here. This is because healthy vegetation was represented by high NDVI values [35], whereas low NDVI was attributed to low-health areas.

Conclusion

The results of this study demonstrate that vegetation indices could contribute to mangrove density mapping for tree health identification area. This study supports the Ramsar convention and Johor National Parks in terms of their conservation activities and in view of a sustainable long-term conservation agenda. The data presented in this study can use as a tool for accelerating and supporting management of the parks. More research is needed to more closely monitor the area and protect it from further industrial development.

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