EVALUATION OF MATANG MANGROVE FOREST LOSS AND GAIN IN 10 YEARS TIME USING MULTI-TEMPORAL SATELLITE DERIVED VEGETATION INDEX

Mohd Fairuz Fuazi, Muhamad Zulfazli Zakaria,
Azlin Azmi

Malaysian Remote Sensing Agency, No 13 Jalan Tun Ismail,
50480 WP Kuala Lumpur, Malaysia
Email: fairuzfuazi@remotesensing.gov.my; zulfazli@remotesensing.gov.my;
azlin@remotesensing.gov.my

KEY WORDS: Mangrove loss and gain, multi-temporal satellite, vegetation index

ABSTRACT: With an area of about 40,288 ha, Matang Mangrove Forest Reserve (MMFR) is recognized as the biggest mangrove forest in Peninsular Malaysia. Almost 75% of its area is productive forest which contributes mangrove poles to charcoal industry in Larut and Matang district. Fisheries and ecotourism sectors also benefited greatly from Matang Mangrove ecosystems. The 10 year period (2010 – 2019) Matang Mangrove working plan was drawn up as a continuation to previous working plans to ensure the ecosystem stability and survival of mangrove related industry in the future. This study was conducted to evaluate mangrove forest loss and gain within the period of current working plan using multi-temporal satellite derived vegetation index. Remote sensing data acquired from SPOT-5, SPOT-6 and SPOT-7 from 2010 to 2019, with the spatial resolution of 2.5m and 1.5m respectively were used to measure forest loss and gain. The vegetation index differencing method (NDVI) was performed on multi-temporal images to identify and quantify areas of significant increase and decrease in NDVI. Results emphasized that mangrove forest cover has recovered steadily from 2010 to 2019, hence proved that the ongoing MMFR management plan is working well to steer Matang mangrove to realise its full potential not only for timber production but also for the ecosystem stability.

1.0 INTRODUCTION

Mangrove is one of the forest types which thrive mainly in sheltered shores, estuaries, rivers and near-shore islands. In Malaysia, mangrove covers about 1.7% (564,606 ha) of Malaysia total area. 17% (97,517 ha) was distributed in Peninsular Malaysia, while the remaining 83% (467,089 ha) in Sabah and Sarawak. Despite having a small coverage, mangrove is recognized to have a large role not only in ecological functionality but also contributing to the local economy through fishing activities, wood and non-wood forest product and eco-tourism industries.

When tsunami hit northern part of Peninsular Malaysia on December 2004, areas with dense mangrove coverage received less tsunami impact compared to areas with less or without mangrove (Keizrul et al., 2005). This proves that mangroves acted as protective barrier against tsunami. The mangrove root systems trap sediments flowing down rivers and off the land. This helps stabilizes the coastline and prevents erosion from waves and storms.

From an economic point of view, mangroves have been utilized by the local communities not only as a source of food, but also as a source of income. Chong (2006) estimated that mangrove forest based economical activities in west coast of Peninsular Malaysia are worth at USD1.38 billion. As for Matang Mangrove Forest Reserve (MMFR), charcoal and poles production generated annual value worth RM53 million, while fisheries activities worth a lot more at RM620 million (Abdul Rahman, 2014).

Over the years, mangrove forests are greatly decreasing due to various factors. It is reported that the world has lost around 3.6 million hectares (ha) of mangrove since 1980, equivalent to an alarming 20 percent loss of total mangrove area (FAO 2007). For Malaysia, the mangrove loss is approximately about 3,500 ha. The main factor contributing to this is unsustainable exploitation of mangroves. For example, mangroves are being converted to coastal development, agriculture and aquaculture. The remaining mangroves are often threatened by water pollution, natural erosion and climate change (https://wwf.panda.org).

Consequently, it is pertinent to know how deterioration of this kind of ecosystem has progressed over time. This would help to more accurately diagnose how degradation progress in the future. Monitoring forest changes including mangrove forest has become a necessity as a result of current environment. Loss and gain from intensive tree cover has a significant impact on the environment and society. Identifying the prospective factors and assessing their significance is crucial.

Generally, the Normalized Difference Vegetation Index (NDVI) was proposed by Rouse et al., (1974) has been used for many years to measure and monitor plant growth, vegetation cover and biomass production from multispectral satellite data (Jackson et al., 1983; Jan et al.,2010) and possible to track the environment. (Desmond et al., 2013) that associate with mangrove ecosystem, Janssen et al., (2018) was detected forest cover change in a nature reserve of central Ghana using the NDVI. Li et al. (2018) used NDVI to examine land cover change in Hangzhou Bay. A research conducted by N. A. Ibrahim et al., (2014), mentioned that a research that took part in Matang Mangrove Forest using the maximum likelihood classifier (MCL) along with NDVI technique. The data acquired was assessed for precision through the Kappa coefficient calculation and the findings revealed that the classification precision was 81.25 percent with 0.78 Kappa Statistics. The research using multi-temporal satellite imageries by Landsat TM and RapidEye.

Furthermore, a study by Meera Gandhi.G et al., (2015) found that the NDVI is highly useful in detecting the surface features of the visible area which are extremely beneficial for policy makers in decision making. The vegetation analysis can be helpful in predicting the unfortunate natural disasters to provide humanitarian aid, damage assessment and furthermore to device new protection strategies. They also mention that change detection analysis is an efficient way of describing the changes observed in each land use category.

This study aims to evaluate Matang mangrove forest lost and gain in 10 years using remote sensing technology through NDVI and NDVI differencing techniques. NDVI is estimated through analysis of satellite images band ratio to give an indication of greenness and healthy forest. By using this method, it provides a better understanding of relationship between mangroves and factors that contribute to the loss and gain. Thus will contribute to more precise estimate of forest loss and productivity in dynamic mangrove ecosystems.

1.1 VEGETATION INDEX

Vegetation indices are among the mostly and extensively studies used in vegetation related application. It is a simple mathematical formula used in remote sensing to estimate the likelihood that vegetation was actively growing at a particular location whenever it was observed (Kalkhan, 2011). It is obtained from multispectral data derived from the difference in absorption, transmittance and reflectance properties of vegetation in the red and near-infrared bands (Fung and Siu, 2000).

Since the used of very first remote sensing satellite, there are huge numbers of vegetation indices have been introduced, going from easy to exceptionally complex band combinations (Bannari et al. 1995). Among others are Ratio Vegetation Index (RVI), Vegetation Index Number (VIN), Differenced Vegetation Index (DVI), Normalized Difference Vegetation Index (NDVI), Transformed Vegetation Index (TVI), Soil Adjusted Vegetation Index (SAVI) and Green Normalized Difference Vegetation Index (GNDVI). In the meantime, the most broadly utilized vegetation indices is NDVI due to its simplicity of calculation and to its affectability to temporal changes in vegetation patterns (Xue & Su, 2017).

NDVI presents the amount of photosynthesizing vegetation. The greater the amount, the brighter the pixel will be. The NDVI is calculated using spectral reflectance measurements acquired in the red and near infrared regions. It is based on band rationing, and calculated from the individual measurements, as follows:

$$NDVI = (NIR - RED) / (NIR) + RED)$$

NDVI values range from -1 to 1 where the positive values show different sorts of vegetation classes, though close to zero and negative qualities demonstrate non-vegetation classes, for example, water, snow, urbanized areas and desolate land (Yacouba et al., 2009). Water, snow, urbanized areas and desolate land are more reflective in the visible band than in the near-infrared and thus have negative NDVI values, whereas the NDVI value of bare soil and rock is around zero. Healthy green vegetation, on the other hand, has greater near-infrared reflectance and thus NDVI values close to +1 (Lillesand et al., 2004).

1.2 STUDY AREA

MMFR is located in the Perak state on the west coast of Peninsular Malaysia. It is the largest mangrove reserves in Peninsular Malaysia and divided into three administrative ranges, namely Kuala Sepetang, Kuala Trong and Sungai Kerang. The current approach divides MMFR into four management zones namely; protective forest, restrictive productive forest, productive forest and unproductive area. Out of the four zones, productive forest is the biggest with

30,120 ha or 75% of the total area (Roslan & Nik Mohd Shah, 2010). Figure 1 shows the boundary of MMFR and extent of the three ranges.

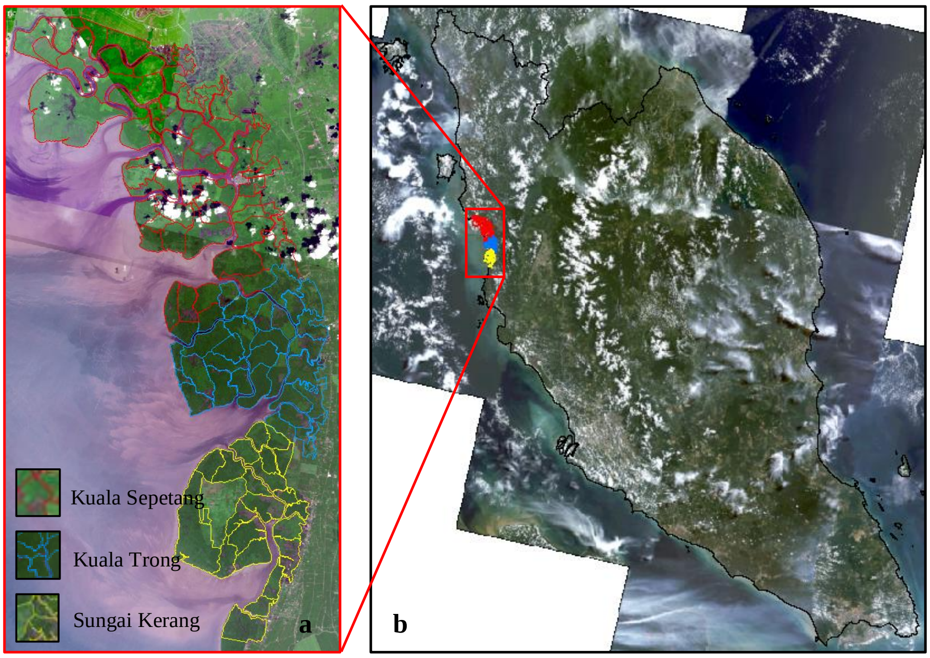

Figure 1. Extent of MMFR (a) and MMFR location on the west coast of Peninsular Malaysia (b)

For the last 100 years, MMFR were managed in a sustainable manner with systematic and comprehensive management practices. The MMFR management is based on a 30-year rotation cycle with two intermediate felling that is carried out in 15 and 20-year stands. This rotation period covered by three 10-year working plan. At the moment MMFR is in its first 10-year period (2010-2019) of the third rotation (2010-2039). After more than a century, the forest is still capable providing numerous good and services to people and environment (Kamaruzaman & Dahlan, 2008). Therefore it is considered as the best-managed mangrove forests in the world (Timber Malaysia, 2009).

The major economic activities in MMFR is charcoal production which are in high demand for overseas market especially from Japan and China. For the period of this working plan, there are 489 allowable charcoal kilns operated in the area with millions ringgit annual production (Roslan & Nik Mohd Shah, 2010). The Matang mangrove also known as a quality poles producer in the country. Poles are harvested during the two intermediate felling and are consigned mainly to the construction industry for pilling and other forms of construction.

1.3 OBJECTIVE

This study was conducted to evaluate MMFR loss and gain within the period of current working plan (2010-2019) using multi-temporal satellite derived vegetation index. The balance in mangrove forest loss and gain is crucial to ensuring that future needs for both the economy and the environment are not much affected.

2.0 MATERIAL AND METHODS

2.1 SATELLITE IMAGES

The study was conducted using multi-temporal satellite imagery of current MMFR working plan in 2010, 2014 and 2019. SPOT-5 pansharpened imagery was used for 2010 obtained on 25th August 2010, while SPOT-6 pansharpened imagery for 2014 obtained on 14th February 2014 and 26th February 2014. Meanwhile, SPOT-6 and SPOT-7 pansharpened imagery were used for 2019 obtained on 25th January 2019 and 19th January 2019. Table 1 shows the information about these five satellite images.

Table 1. Satellite data characteristics used in this study

Satellite sensor	Acquisition date	Spatial resolution (m)	Cloud cover (%)	Spectral bands
SPOT-5	25 August 2010	2.5	14	0.50-0.59µm (Green band) 0.61-0.68µm (Red band) 0.78-0.89µm (NIR band) 1.58-1.75µm (SWIR band)
SPOT-6	14 February 2014	1.5	10	0.45-0.52µm (Blue band) 0.53-0.59µm (Green band) 0.63-0.70µm (Red band) 0.76-0.89µm (NIR band)
SPOT-6	26 February 2014	1.5	3	
SPOT-6	25 January 2019	1.5	10	
SPOT-7	19 January 2019	1.5	16	

*SWIR = short-wave infrared; NIR = near infrared

2.2 IMAGE PREPARATION AND PROCESSING

Generally, there were three steps used in this study as shown in Figure 2. Prior to image processing, the acquired images need to be pre-processed, that are radiometric and geometric correction. Radiometric corrections were applied to the images for removing radiometric defects and improving the visual impact of the data. Geometric rectification of the data was carried out with the help of Ground Control Points (GCP) for assigning geographical coordinates to keep the pixel of the image. All images were then re-projected into Kertau Rectified Skewed Orthomorphic (RSO) projection to match with the Malaysia topographic mapping system. Then the images were subset to the MMFR boundary to reduce the file size and improving the processing times.

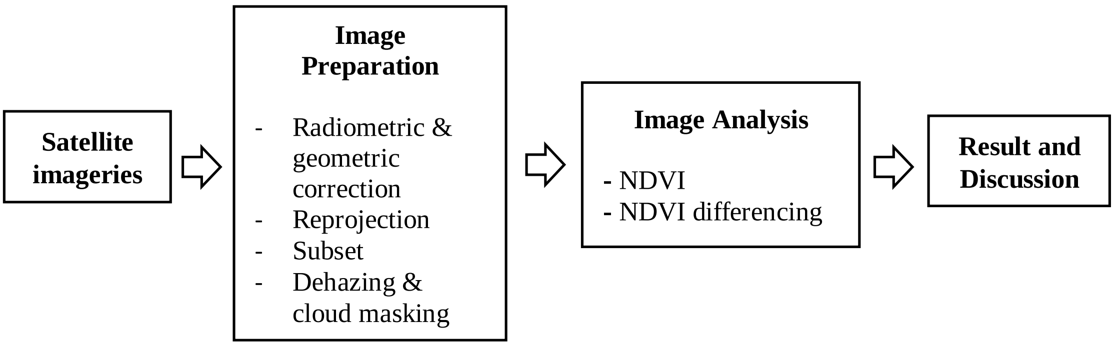

Figure 2. Workflow of the methodology adapted in this study

In optical remote sensing study especially in tropical area, there is some weakness that which cannot be avoided, that is cloud cover. It is one of the significant obstacles in extracting information using optical remote sensing (Wang et al., 1999). Some part of MMFR areas in the images used in this study covered with cloud, shadow and haze, therefore covered the information in that part of the image. To remove the cloud, shadow and haze, cloud masking and dehazing has been done to this images. The masked cloud areas were filled in with clear view surfaces from other images.

Then NDVI was calculated for each images using equation shown in section 1.1. NDVI use band 2 (Red) and band 3 (Near infrared) for SPOT-5, band 3 (Red) and band 4 (Near infrared) for SPOT-6 and SPOT-7. The NDVI layers were in white/black colour presenting the amount of vegetation present at each images. It is then classified into five classes. To easily spot the high and low values of the index, the classified layers were color coded to Fir Green for dense vegetation, Leaf Green for moderate dense, Quetzel Green for lower dense, Medium Apple for lowest dense and Mars Red for non-vegetation.

Based on the results, the three year NDVI images were reclassified into five classes. Class 1 indicates non vegetation, class 2 for lowest dense, class 3 for lower dense, class 4 for moderate dense and class 5 for dense vegetation. Reclassification is the process of reassigning a value, a range of values, or a list of values in a raster to new output values. In this study, NDVI images were reclassified to simplify the information so that area of each classes can be measured and evaluated.

Vegetation change in the study areas were measured by comparing NDVI value of year 2010 with NDVI value of year 2014 and NDVI value of year 2014 with NDVI value of year 2019. This technique is called as NDVI differencing method, where NDVI values are compared and calculated from different images (Mancino et al., 2014). In order to apply NDVI differencing, the individual NDVI image of each year was produced with a range of values from -1 to 1. In this study, the 2010 NDVI was subtracted from the 2014 NDVI, while 2014 NDVI was subtracted from the 2019 NDVI. It is described as follows:

$$\Delta NDVI = NDVI_{2014} - NDVI_{2010}$$
$$\Delta NDVI = NDVI_{2019} - NDVI_{2014}$$

A threshold method based on differencing image histogram was chosen to identify mangrove forest loss and gain. In this technique, the significant changes were discovered in the tails of the histogram distribution whereas pixels showing no significant change tended to be clustered around the means (Singh, 1989). The first stage was to select the threshold, where zero is deemed to be non-change area while values greater or smaller than zero are deemed to be changing areas. Then the first standard deviation ($\mu \pm 1\ \sigma$) was selected to identify changes. Finally, forest loss and gain map was created between 2010-2014 and between 2014-2019.

3.0 RESULTS AND DISCUSSION

3.1 GENERAL TREND OF NDVI

Figure 3 shows the NDVI results for the year of 2010, 2014 and 2019 in color coded. The result indicates that dense vegetation NDVI values fall at 0.45 and above, moderate dense values range between 0.3 to 0.45, lower dense from 0.15 to 0.3, lowest dense from 0 to 0.15, while non vegetation NDVI values fall at 0 and lower. Increasing positive values show increasing green vegetation cover and negative values show non-vegetated features like logged over areas, bare lands and water bodies. Areas of healthy vegetation are green, while yellowish areas indicate little vegetation, and areas without no vegetation are red.

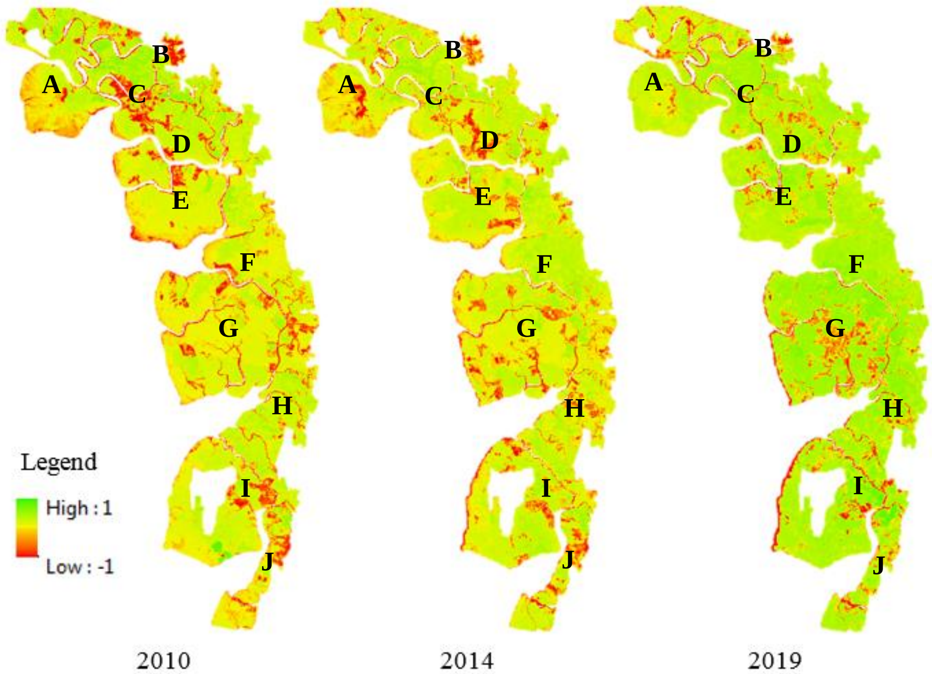

Figure 3. NDVI results for 2010, 2014 and 2019

The green area which represents vegetated areas has greater near-infrared reflectance. This implies that most of the visible light was used to produce biomass thereby resulting NDVI values ranging from 0.3 to 1. This represents areas of plants with good condition, high leaf biomass, canopy closure and high chlorophyll content of vegetation (Wang et al., 2004). In contrast, negative NDVI values were recorded in red area. This is because features are more reflective in the visible band than in the near-infrared band, showing low vegetation areas, typical water, cloud, bare soil and rock (Lillesand, 2004). Comparatively, from Figure 3, it is seen that 2019 has greater proportion of vegetation cover followed by 2014 and 2010. Its reveal that most harvesting areas that took place before 2019 have grown steadily, therefore forest conditions have begun to stabilize. For 2010, only a few areas (mostly in Kuala Sepetang range) have high NDVI values, while the rest of areas with average and low NDVI values. In 2014, some of areas with low NDVI values in 2010 has slightly higher NDVI values meaning that vegetation growth process is taking place. On the contrary, there are some areas where have decreasing NDVI values. This means that harvesting process at that areas are in progress or represent regions with young vegetated area.

Table 2 specifically shows areas in Figure 3 with increase and decrease of NDVI values. Area A relatively has low NDVI value decrease from 0.016 in 2010 to -0.056 in 2014 but increase to 0.167 in 2019. Similar behavior is observed at area D, E and H whereby NDVI decrease from 2010 to 2014 but increase from 2014 to 2019. This behavior indicates that those areas have been harvested in 2014 and being regenerated within the period of 2014-2019. Area B, C, F, I and J showing improvement of NDVI values from 2010 to 2014 and to 2019 indicating harvesting process took place in 2010 or earlier. Contrarily, area G shows decreasing of NDVI values from 2010 to 2014 and to 2019. This is due to the fact that this area is under harvesting process from the period of 2010-2019.

Table 2. Increase and decrease of NDVI values of specific area in 2010, 2014 and 2019

Year	NDVI values									
	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**
2010	0.016	0.043	0.187	0.504	0.438	0.418	0.507	0.435	0.146	0.156
2014	-0.056	0.152	0.476	0.290	0.133	0.471	0.355	0.384	0.375	0.182
2019	0.167	0.243	0.500	0.545	0.556	0.500	0.154	0.600	0.500	0.333

3.2 ANALYSIS OF FOREST LOSS AND GAIN

The area of each density classes in the year 2010, 2014 and 2019 are shown in Table 3. As it can be seen in this table and Figure 4, the most large dense classes is dense vegetation in 2010 and 2019. That class is more than 57% of total area. Second large area is moderate dense with more than 24% of total area. In contrast, for 2014, moderate dense class is the biggest with 53.15% of total area, while lower dense is second large with 20.15% of total area. Considering moderate dense class (NDVI values: 0.3-0.45) and dense vegetation class (NDVI values: ≥ 0.45) as good and healthy forest condition, 2010 has 34,996.38 ha of good forest condition or 86.6% of MMFR total area, 2014 has 26,951.19 Ha of good forest condition or 66.72% of MMFR total area and 2019 has 36,543.66 ha of good forest condition or 90.46% of MMFR total area.

Table 3. Area of density classes for 2010, 2014 and 2019

No	Dense classes	2010		2014		2019	
		Area (Ha)	%	Area (Ha)	%	Area (Ha)	%
1	Non vegetation	189.97	0.47	1,996.55	4.94	928.22	2.30
2	Lowest dense	3,026.90	7.49	3,307.85	8.19	1,160.81	2.87
3	Lower dense	2,199.17	5.44	8,141.75	20.15	1,762.88	4.36
4	Moderate dense	11,903.97	29.46	21,470.36	53.15	10,075.25	24.94
5	Dense vegetation	23,092.41	57.14	5,480.83	13.57	26,468.41	65.52
	Total	40,412.42	100.00	40,397.34	100.00	40,395.56	100.00

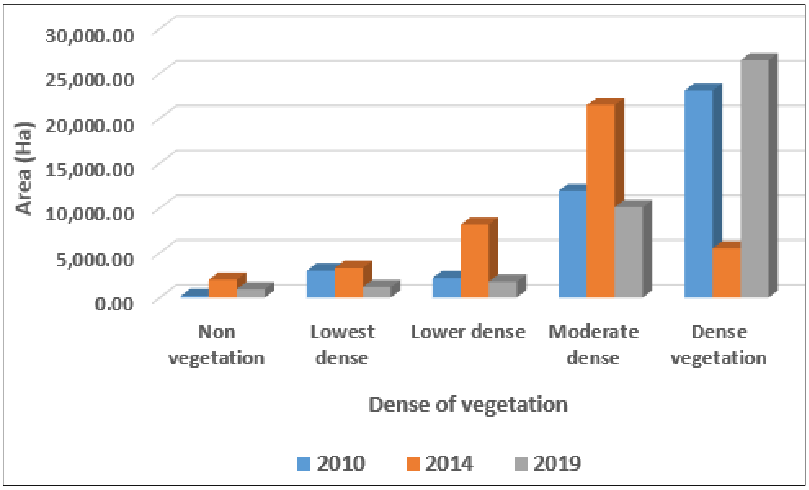

Figure 4. Changes of forest density for 2010, 2014 and 2019

The vegetation changes in the MMFR between 2010 and 2014 and between 2014 and 2019 are shown in Table 4 (a) and Table 4 (b), respectively. The change is calculated by comparing the values of plant density between 2010 and 2014 and 2014 and 2019. The previous year was defined as the base year. For the period 2010-2014, the rate of change in forest density varied between density classes. Table 4 (a) shows the increase of non-vegetation area of approximately 1,806.58 ha. Lowest dense, lower dense and moderate dense areas increased by 280.95 ha, 5,942,58 ha and 9,566,39 ha respectively. There was a decrease of 17,611.58 ha in the dense vegetation area at a rate of 4,402.90 ha / year. This decline may be attributed to a steady increase in the area of moderate dense vegetation which indicates that the area is slowly recovering from the harvesting activity. Harvesting activities is believed to be active within this period as 33.28% of the green land has been transformed into low and non-vegetation area.

The changes between 2014 and 2019 as revealed in Table 4 (b) shows an increase of 20,987.58 ha of dense vegetation area or equivalent to 4,197.52 ha / year. Vegetation gain mainly concentrated in areas far from the coast. The remaining classes shows decreases where the vegetation density for the non-vegetation area recorded a decrease of 1,068.33 ha followed by the lowest dense 2,147.04 ha, lower dense 6,378.87 ha and moderate dense 11,395.11 ha. These changes represent a positive indication that vegetation cover in MMFR from 2014 to 2019 has begun to grow at a satisfactory rate.

Table 4(a). Forest density changes between 2010-2014

No.	Dense classes	Area (Ha)		Area (Ha)		Rate (Ha/year)
		2010	2014	Increased	Decreased	
1	Non vegetation	189.97	1,996.55	1,806.58	-	451.64
2	Lowest dense	3,026.90	3,307.85	280.95	-	70.24
3	Lower dense	2,199.17	8,141.75	5,942.58	-	1,485.65
4	Moderate dense	11,903.97	21,470.36	9,566.39	-	2,391.60
5	Dense vegetation	23,092.41	5,480.83	-	17,611.58	4,402.90

Table 4(b). Forest density changes between 2014-2019

No.	Dense classes	Area (Ha)		Area (Ha)		Rate (Ha/year)
		2014	2019	Increased	Decreased	
1	Non vegetation	1,996.55	928.22	-	1,068.33	213.67
2	Lowest dense	3,307.85	1,160.81	-	2,147.04	429.41
3	Lower dense	8,141.75	1,762.88	-	6,378.87	1,275.77
4	Moderate dense	21,470.36	10,075.25	-	11,395.11	2,279.02
5	Dense vegetation	5,480.83	26,468.41	20,987.58	-	4,197.52

After differential assessment on both 2010-2014 and 2014-2019 NDVI results, the differences between the loss and gain of mangrove forest density areas are clearly shown in Figure 5. The green and red colors are assigned to areas that have experienced changes, while black indicates areas with little or no changes. The red areas are region that have lost its vegetation density while green areas represent the gain in vegetation density for the period 2010-2014 and 2014-2019. There were about 12,195.09 ha of vegetation density area loss in the period of 2010 to 2014 accounting for 30.18% of total MMFR area. The decrease in vegetation density was offset by an increase in cover of dense vegetation in the 28,175.40 ha area and resulted in a net gain of 15,980.31 ha, or 39.54% of native mangrove area. Meanwhile, the area of 41.93 hectares remained unchanged.

Results in the period of 2014 and 2019 (Figure 5b) show an increase of vegetation density in the MMFR area of 34,367.23 ha, which is 85.07% of the total area. At the same time, there was a loss of plant density in the area of 6.012.45 ha which is equivalent to 14.88% of MMFR area. Based on current MMFR working plan, this loss is due to harvesting activities constitute thinning and clear felling operations. Meanwhile, 0.01 ha areas remain unchanged which is not significant. This patterns of vegetation density change are normal for mangroves considering 75% of MMFR area are productive forest and are managed under a systematic management plan. Summarily, this behaviour means the ongoing management of MMFR which is at the end of the first 10-year period of the third rotation and also identified as the best managed mangrove forest in the world is capable to meet the needs of the economy and the ecosystem.

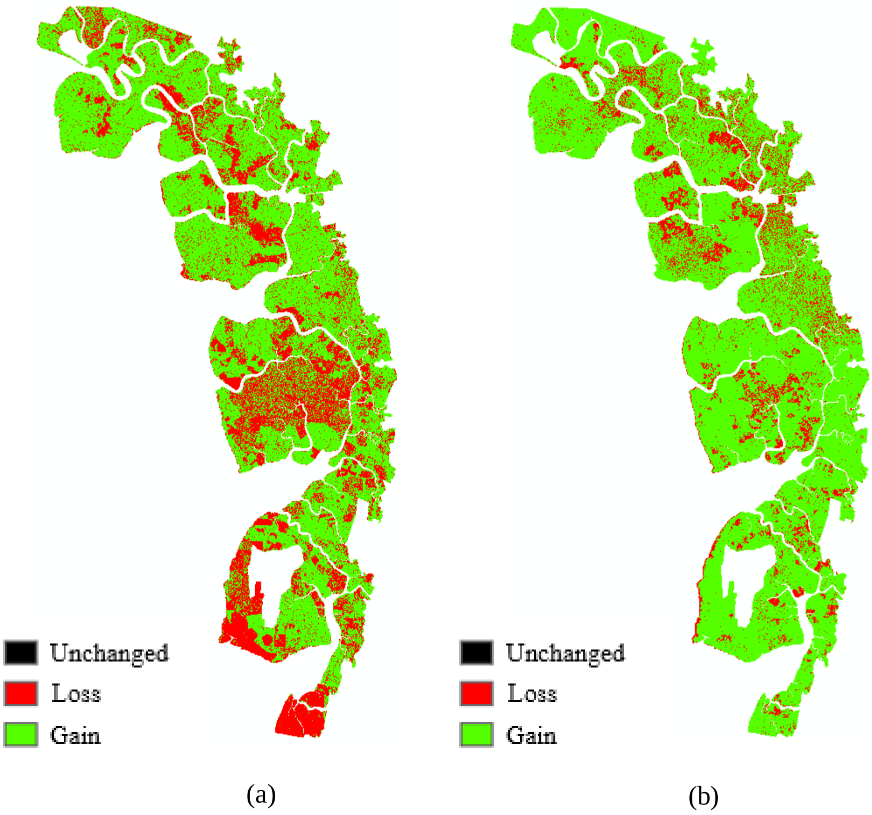

Figure 5. Mangrove forest loss and gain map between 2010-2014 (a) and 2014-2019 (b)

4.0 CONCLUSIONS

This study demonstrated how satellite-based detection of vegetation change can provide reliable results in the assessment and evaluation of mangrove forest loss and gain over time. The NDVI analysis and NDVI differencing techniques can be employed to evaluate the vegetation cover and hence to monitor the forest cover dynamics. Although these process can be made more effective and accurate with presence of ground truth data and accuracy assessment, the results of this study are still presentable. The results also emphasized that mangrove forest cover has recovered steadily from 2010 to 2019, hence proved that the ongoing MMFR management plan is working well to steer Matang mangrove to realise its full potential not only for timber production but also for the conservation of biodiversity, protection of flora and fauna and marine resources, and the socio-economic well-being of the communities. This study also provides opportunities for future studies in monitoring Matang mangrove vegetation loss and gain based on harvesting operation and mangrove tree species supported by accuracy assessment.

5.0 ACKNOWLEDGMENT

This study is joint project between Malaysian Remote Sensing Agency (MRSA), Forestry Department of Peninsular Malaysia (FDPM) and Perak State Forestry Department (PSFD). We would like to express our appreciation to the Director General of MRSA, FDPM and PSFD who have consistently encouraged our effort and all parties involved directly or indirectly in this study.

6.0 REFERENCES

Abdul Rahman Abdul Rahim, 2014. The Future Prospects of Managing Matang Mangrove Forest for Community Livelihood. Paper presented at Matang mangrove Forest Management Conference, 24-25 November 2014.

Bannari, A., Morin, D., Bonn, F. & Huete, A. R., 1995. 'A review of vegetation indices', Remote Sensing Reviews, 13(1), pp. 95-120.

Chong, V. C., 2006. Sustainable utilization and management of mangrove ecosystems of Malaysia. Aquatic Ecosystem Health & Management 9(2), pp. 249-260.

Desmond Ofosu Anim, Amos Tiereyangn Kabo-bah, Philip Nti Nkrumah, & Raphinos Tackmore Murava, 2013. Evaluation of NDVI Using SPOT-5 Satellite Data for Northern Ghana. Environmental Management and Sustainable Development, 2(1), pp. 167-182.

FAO, 2007. The World's Mangrove 1980-2005. A Thematic Study Prepared in the Framework of the Global Forest Resources Assessment 2005. FAO forestry paper no. 153. Rome, Italy.

Fung, T, & Siu, W., 2000. Environment Quality and it's Changes, an Analysis Using NDVI, International Journal of Remote Sensing, 21(5), pp. 1011-1024.

Jackson, R. D., Slater, P. N., & Pinter Jr, P. J., 1983. Discrimination of Growth and Water Stress in Wheat by Various Vegetation Indices through Clear and Turbid Atmospheres. Remote Sensing of Environment, 13(3), pp. 187-208.

Jan, U. H. Eitel, Robert, F. Keefe, Dan, S. Long, Anthony, S. Davis & Lee, A. Vierling, 2010. Active Ground Optical Remote Sensing for Improved Monitoring of Seedling Stress in Nurseries. Sensors, 10, pp. 2843-2850.

Janssen, T.A.J., Ametsitsi, G. K. D., Collins, M., Adu-Bredu, S., Oliveras, I., Mitchard, E. T. A., & Veenendaal, E. M., 2018. Extending the baseline of tropical dry forest loss in Ghana (1984–2015) reveals drivers of major deforestation inside a protected area. Biological Conservation. 218, pp. 163–172.

Jinru Xue and Baofeng Su, 2017. Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. Journal of Sensors, vol. 2017, Article ID 1353691, 17 pages.

J. Wang, P. M. Rich, K. P. Price & W. D. Kettle, 2004. Relations between NDVI and tree productivity in the central Great Plains, International Journal of Remote Sensing, 25(16), pp. 3127-3138.

Kalkhan, M. A., 2011. Spatial statistics: Geospatial information modeling and thematic mapping. Boca Raton, FL: CRC Press.

Kamaruzaman Jusoff & Dahlan Taha, 2008. Managing Sustainable Mangrove Forests in Peninsular Malaysia. Journal of Sustainable Development, 1.

Keizrul Abdullah, Tan, K. S., & Ghazali, N. H. M., 2005. No More In The Comfort Zone – Malaysia's Response to the December 2004 Tsunami. Paper presented at International Hydrography and Oceanography Conference and Exhibition, 3-7 July 2005.

Li DQ, Lu DS, Wu M, Shao XX, & Wei JH, 2018. Examining land cover and greenness dynamics in Hangzhou Bay in 1985–2016 using Landsat time-series data. Remote Sensing, 10(1), pp. 22.

Mancino, G., Nole, A., Ripullone, F., & Ferrara, A., 2014. Landsat TM imagery and NDVI differencing to detect vegetation change: assessing natural forest expansion in Basilicata, southern Italy. Iforest, 7, pp. 75-84.

Mangrove Forests are on of The World's Most Threatened Tropical Ecosystems, from https://wwf.panda.org/our_work/oceans/coasts/mangroves/mangrove_threats/

Meera Gandhi, G., S., Parthiban, Nagaraj Thummalu, A., Christy, 2015. Vegetation change detection using remote sensing and GIS - A case study of Vellore District. Procedia Computer Science, 57, pp. 1200-1210.

N. A. Ibrahim, M. A. Mustapha, T. Lihan, & M. A. Ghaffar, 2013. Determination of Mangrove Change in Matang Mangrove Forest Using Multi Temporal Satellite Imageries; School of Environment and Natural Resource Sciences, Faculty of Science and Technology, Universiti Kebangsaan Malaysia. AIP Conference Proceeding. Pp. 487-492.
Richards, D. R., & Friess, D. A., 2016. Rates and drivers of mangrove deforestation in Southeast Asia, 2000-2012. Proceedings of the National Academy of Sciences of the United States of America, 113(2), pp. 344–349.

Roslan Ariffin & Nik Mohd Shah Nik Mustafa, 2010. A Working Plan for the Matang Mangrove Forest Reserve, Perak. The first 10-year period (2010-2019) of the third rotation. Perak Forestry Department.

Rouse, J. W., Haas, R. H., Schelle, J. A., Deering, D. W., & Harlan, J. C., 1974. Monitoring the Vernal Advancement or Retrogradation of Natural Vegetation. NASA/GSFC, Type III, Final report, Green-belt, MD.

Singh, A., 1989. Digital change detection techniques using remotely-sensed data. International Journal of Remote Sensing 10, pp. 989-1003.

T. M. Lillesand, R. W. Kiefer and J. W. Chipman, 2004. Remote Sensing and Image Interpretation. 5th Edition, John Wiley & Sons, Inc., New York.

Timber Malaysia, 2009. Vol. 15 No.3 May – June 2009. Malaysian Timber Council. Matang Mangrove: A Century of Sustainable Management.

Wang, B., Ono, A., Muramatsu, K., & Fujiwara, N., 1999. Automated detection and removal of clouds and their shadows from Landsat TM images. IEICE Transactions on Information and Systems E82- D, 453–60.

Yacouba, D., Guangdao, H., & Xingping, W., 2009. Assessment of Land Use Cover Change Using Ndvi and Dem Inpuer and Simao Counties, Yunnan Province, China. World Rural Observations, 1(2), pp. 1-11.