MANGROVE FOREST CHANGE IN NUSA PENIDA MARINE PROTECTED AREA, BALI - INDONESIA USING LANDSAT SATELLITE IMAGERY

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Abstract. Nusa Penida, Bali was designated as a Marine Protected Area (MPA) by the Klungkung Local Government in 2010 with support from the Ministry of Marine Affairs and Fisheries, Republic of Indonesia. Mangrove forests located in Nusa Lembongan Island inside the Nusa Penida MPA jurisdiction have decreased in biomass quality and vegetation cover. It's over the last decades due to influences from natural phenomena and human activities, which obstruct mangrove growth. Study the mangrove forest changes related to the marine protected areas implementation are important to explain the impact of the regulation and its influence on future conservation management in the region. Mangrove forest in Nusa Penida MPA can be monitored using remote sensing technology, specifically Normalized Difference Vegetation Index (NDVI) from Landsat satellite imagery combined with visual and statistical analysis. The NDVI helps in identifying the health of vegetation cover in the region across three different time frames 2003, 2010, and 2017. The results showed that the NDVI decreased slightly between 2003 and 2010 but increased significantly in 2017, where a mostly positive change occurred landwards and adverse change happened in the middle of the mangrove forest towards the sea.

Keywords: *mangrove changes, Nusa Penida MPA, remote sensing, NDVI*

1 INTRODUCTION

Deforestation and forest degradation has become a major global issue, especially in light of climate change, global warming, and other environmental factors. Global Forest Change analysis has shown global deforestation around the world, whereas Indonesia exhibited an enormous loss in forest approximately 1,021 km^2/year (Hansen *et al.* 2013), with total primary forest loss estimated at over 60,200 km^2 between 2002 and 2012 and increased on average by 470 km^2/year (Margono *et al.* 2014).

Indonesia is renowned for the largest mangrove forests in the world, which have decreased from 42,000 km^2 to less than 31,100 km^2 (Giri *et al.* 2011). Deforestation and forest degradation in Indonesia mostly caused by human intervention and commercial purposes such as agriculture, aquaculture, tourism, coastal development, and other purposes (Kissinger *et al.* 2012, Spalding 2010). Mangrove forests are found in tropical and subtropical regions providing several ecosystem services such as; spawning, breeding, hatching and nursery ground for many living fauna (Cannicci *et al.* 2008). They also provide construction materials, food, and fuel (Rönnbäck *et al.* 2007), and social value

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such as cultural sites and recreational purposes (Giri *et al.* 2011). In addition, they have been cited for reducing tsunami impact (Kathiresan and Rajendran 2005), protecting the shoreline of coastal communities (Gedan *et al.* 2011), and reduce the impact of global climate change through carbon storage (Alongi 2008, Alongi *et al.*, 2016 Donato *et al.* 2011, Murdiyarso *et al.* 2015). Mangroves are renowned as productive ecosystems which provide both ecological and socio-economic benefit (Alongi 2002, Walters *et al.* 2008). Mangrove forest in Nusa Lembongan located inside the Nusa Penida Marine Protected Area (MPA) which purposes of conserving biodiversity, economic resources and much more by creating an area of specific regulation (Dudley 2008). The management of MPAs in Indonesia controlled by the Ministry of Marine Affairs and Fisheries, the Ministry of Environment and Forestry, and Local Government (Nurhidayah and Alam 2017, Dirhamsyah, 2016) (Table 1-1).

Kusumaningtyas *et al.* (2014) conducted a blue carbon stock study in Nusa Penida MPA mangrove ecosystems and found five dominant mangrove species in the region with density from 100 to 2620 tree/ha and potential to store carbon up to 14,29 MgC, and CO_2 absorbed around 54,792. Mg CO_2e. They estimated the mangrove forest cover in the Nusa Penida MPA using Landsat 7 ETM+ with NDVI technique and measured approximately 164.5 ha. The previous study by Widagti *et al.* (2011) mapped the Nusa Penida region using ALOS AVNIR-2 (Advanced Land Observing Satellite) with 10-meter resolution (ALOS 2017) resulted in the mangrove coverage decrease by 47.09 ha within two years with variation in density change. Both of the researches explained the recent condition of the mangrove forest in Nusa Lembongan Island as part of Nusa Penida MPA after the implementation. Therefore, it is important to analyze the condition before and after the MPA implementation, and as an update data and information regarding the mangrove forest.

The proposed research will integrate remote sensing technology with site observations to monitor the spatial and temporal changes in the mangrove forest coverage and density in Nusa Lembongan from 2003 to 2017. Satellite images of Nusa Penida region in 2003 were chosen as a point when tourism increased significantly in Bali, resulting in massive economic activities in the study area over the years between 2003 and 2010.

Table 1-1: Indonesian Marine Protected Areas

No	Conservation Areas	Ministry of Forestry	Ministry of Marine Affairs and Fisheries	Area (km^2)
1	Marine National Park	7	1	75,646.71
2	Marine Recreation Park	14	6	20, 322.88
3	Wildlife Reserve	5	0	56.78
4	Marine Nature Reserve	6	3	6,001.10
5	Marine Protected Area	0	89	55,614.63
	Total	32	99	157,642.10

(Source: Suraji 2014)

Besides 2010 to present (2017) was chosen as the period during which an MPA was designated and enforced in the region by the government. This research examines the condition of mangrove forest regarding the implementation of Nusa Penida MPA in the region.

2 MATERIALS AND METHODOLOGY

2.1 Site Location

Nusa Penida (Figure 2-1(a)) administratively under the authority of Klungkung District, Bali Province, which famous for its natural resources potencies such as tourism, aquaculture, and fisheries. Nusa Penida consisted of three islands where Nusa Penida is the biggest island compared to other two islands such as Nusa Lembongan and Nusa Ceningan with the total area around 202,84 km^2 and population 46,749 people (Central Bureau of Statistics, 2017). Nusa Penida located apart from Bali island and considered as an area with high marine biodiversity based on its location in Lombok straits as one of the Indonesia Through-Flow (ITF) from the Pacific Ocean to Hindian Ocean through Makassar Straits (Gordon *et al.* 1999, Murray and Arief, 1988). Several National and international collaborations established in Nusa Penida including Blue Economy Project proposed by the Ministry of Marine Affairs and Fisheries, Republic of Indonesia (The Jakarta Post 2014), and Blue Solutions Project with IUCN (2014).

The Nusa Penida MPA (Figure 2-1(b)) was implemented by applying several restriction zoning systems with specific restriction including core zone (no take zone), special tourism zone, sustainable.

Fishery zone, seaweed farming zone, marine tourism zone, sacred zone, and utilization zone. The MPA's main purpose is to establish and protect the marine biodiversity of the area and reduce conflict among these resource users for the benefit of local communities (Weeks *et al.* 2014).

2.2 Materials

This study relies on the utilization of Landsat satellite imagery with 15 years observation started from 2003 until 2017, which divided into three different time frames with seven years gap. The surface reflectance of Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 (Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)) from USGS database used for this study. Landsat 7 ETM + and Landsat 8 (OLI and TIRS) have the same characteristics in sensors, correction methods, and resolution: spatial, temporal, and spectral with repeat 16 days, coverage 170 km X 183 km, and 30-meter resolution (USGS, 2017). They also have similar correction methods and sensors characteristics (Table 2-1).

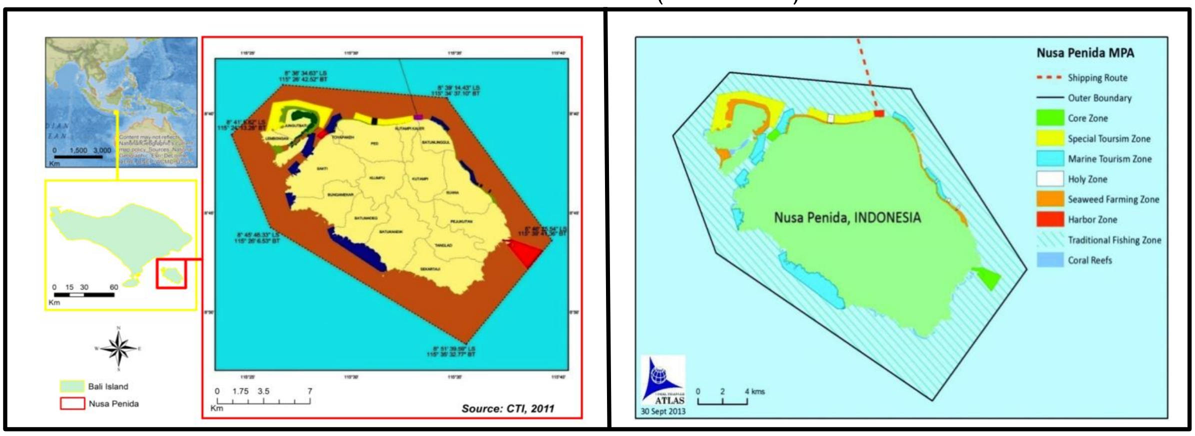

Figure 2-1: Nusa Penida administrative (a) Nusa Penida MPA (b), Bali – Indonesia

Table 2-1: Landsat 7 ETM+ and Landsat 8 (OLI and TIRS sensors)

No	Landsat 7 ETM Bands	Landsat 7 ETM+ Wavelength (µm)	Landsat 8 OLI-TIRS Wavelength (µm)	Landsat OLI-TIRS Bands
1			0.435-0.451	Band 1 30 m Coastal/Aerosol
2	Band 1 30 m Blue	0.441-0.514	0.452-0.512	Band 2 30 m Blue
3	Band 2 30 m Green	0.519-0.601	0.533-0.590	Band 3 30 Green
4	Band 3 30 m Red	0.631-0.692	0.636-0.673	Band 4 30 m Red
5	Band 4 30 m NIR	0.772-0.898	0.851-0.879	Band 5 30 m NIR
6	Band 5 30 m SWIR	1.547-1.749	1.566-1.651	Band 6 30 m SWIR-1
7	Band 6 30 m TIR	10.31-12.36	2.107-2.294	Band 7 30 m SWIR-2
8	Band 7 30 m SWIR-2	2.064-2.345	0.503-0.676	Band 8 15 m Pan
9	Band 8 15 m Pan	0.515-0.896	1.363-1.384	Band 9 30 m Cirrus
10			10.60-11.19	Band 10 100 m TIR-1
11			11.50-12.51	Band 11 100 m TIR-2

(Source: USGS 2017)

Even though there is a slight difference in length of the light spectrum (spectral range) between two satellites, where most of the bands in Landsat 8 OLI narrower than Landsat 7 ETM+, but the utilization of the visible bands especially for NDVI is not affected so much (Jensen 2015). It's only to create a better visualization for vegetated and non-vegetated area (Irons *et al.* 2012).

2.3 Methods

The research activities in monitoring mangrove forest change utilized the images from Landsat 7 ETM+ and Landsat 8 (OLI and TIRS) from three different years, where Landsat 7 ETM+ used for 2003 and 2010, while Landsat8 OLI and TIRS for 2017 (USGS, 2017). The satellite images in 2010 are used as the references in which the MPA designation begins, while the satellite images from 2003 (pre-designation) and 2017 (after designation) used as the comparison for mangrove forest monitoring before and after the MPA implementation. Several steps conducted in this study such as Image Processing, Image Analysis, and Image Visualization (Figure 2-2).

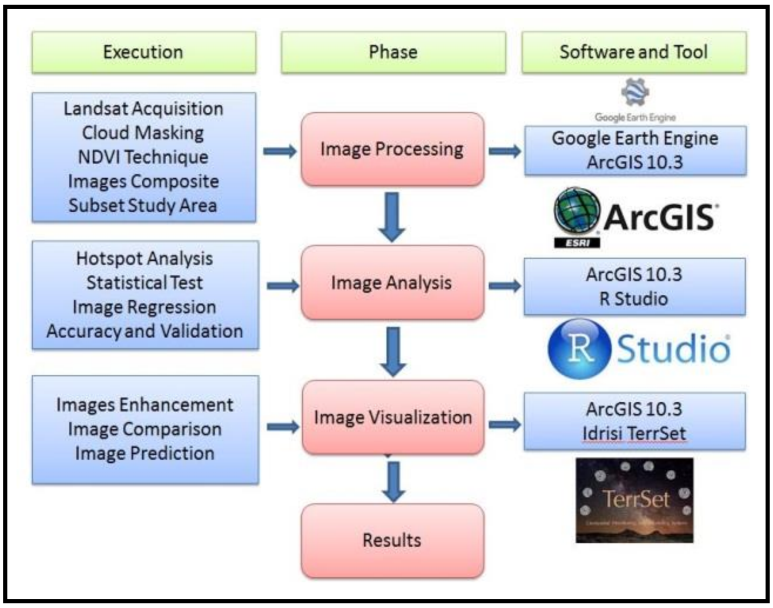

Figure 2-2: Flowchart of methodological process

2.3.1 Image Processing

Its multi-temporal, long-term availability, and study length observation, which freely used under the USGS authorization, made Landsat satellite images were chosen as the main dataset (Wulder *et al.* 2012).

Satellite imagery acquisition gathered using Google Earth Engine Application Program Interface (GEE-API) (Gorelick *et al.* 2017), by generating satellite images within two years for each chosen time frame and creating layer stack of images known as image collection. CFMask as the C language version of Mask algorithm function used to generate a cloud mask to standardize dataset from images with high intensity of cloud cover, which have the best overall accuracy compared to other algorithms (Foga *et al.* 2017).

Normalized Difference Vegetation Index (NDVI) is to determine mangrove classification based on its index value, which indicates the presence of green plants and the vegetation health index around the study area utilizing visible Red band combined with Near-Infrared band from the chosen satellite imagery. NDVI value ranging between -1 and +1 where the higher value (positive) showed the high quality of vegetation, while small value (negative) of NDVI indicates non-vegetation (Mather and Koch 2011). NDVI assessed by combining the visible Red and Near-infrared (NIR) light reflected by vegetation and display healthy vegetation that absorbs the most incoming visible light and reflects most of the near-infrared light, and so the opposite for unhealthy vegetation written mathematically as:

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \tag{2-1}$$

Where,

NDVI = Normalized Difference Vegetation Index

NIR = Near Infrared canal

Red = Red Canal

Google Earth Engine used to generate the NDVI from image collection and composite the NDVI image collection using reducer section by it median value to reduce noise from “salt and pepper” and avoid outliers in the dataset (Toh *et al.* 2008, Wang and Zhang 1999, Bhosale and Manza 2013).

2.3.2 Image Analysis

Several methods used to analyze the satellite images by describing image characteristics, spatial distributions, examine the images using statistical approaches, and image regression. Lastly, accuracy assessment conducted to support the results of the study.

Hotspot analysis performed to identify statistically significant spatial cluster of high values (hotspots) and low values (cold spots) from pixel values between time frames, it also determine the spatial correlation between images based on its pixel values and distinguish the spatial distribution from the dataset in confidence level 99%, 95%, and 90%. Hotspot analysis for each time frame executed using spatial analysis feature in ArcGIS 10.3 Getis-Ord GI* (Nallan *et al.* 2015).

Statistical analysis performed to examine the characteristics of dataset statistically, and determine the relationship among dataset from three different time frames by generating a regression model. Paired T-test performed to determine statistical evidence related to the mean difference between paired observations or to distinguish the significance of treatment between images in a different time observation.

Image regression implemented to produce statistical information, relationship, and the correlation coefficient between two different images. The first regression analysis compared the points value of observed images from 2003 and 2010, while the second regression analysis compared the points value observed image from 2010 and 2017 (Eastman 2016).

Accuracy Assessment and error performed on image classification to determine the level of accuracy based on task achievements. The classification ordered to verify the mangrove forest and non-mangrove forest by utilizing the georeferencing and rectification technique of Google Earth High-Resolution image to study area. The accuracy assessment used Cohen's kappa coefficient as the coefficient of agreement between inter-rater which combined the proportions and frequencies among sample units and determine the significance, degree, and stability for illustration (Cohen 1960).

$$K = \frac{\text{Observed} - \text{Expected}}{1 - \text{Expected}} \tag{2-2}$$

Where:
K = Kappa Coefficient
Observed = Total number of correct observed points
Expected = Total number of correct expected points

2.3.3 Image Visualization

Visualization of the results carried out by enhancing the images to simplify the contrast for better analysis and precise comparison. Image projection was undertaken by applying the equation resulted from statistical analysis and image regression to new images and compared the condition with or without MPA.

3 RESULTS AND DISCUSSION

The map shows mangrove forest health index (Figure 3-1) for three different time frames in Nusa Lembongan island, where the brightest green to red represents the negative value that indicates non-vegetation cover, while the positive value represented by darker green displayed mangrove vegetation cover.

Time Frame 1 (2003) used the image collection from 2002 – 2003 combination, resulted in 23 images with least cloud cover 4%, Time Frame 2 (2010) from 2009 – 2010, resulted in 17 images with least cloud cover 0.15%, while Time Frame 3 (2010) used the image collection from 2016 – 2017, resulted in 25 images with the least cloud cover 1.7%. This technique used to avoid outliers within the observation and stripes problem occurred in Landsat 7 ETM+ after the 2003 incident (SLC off) that may distract the analysis.

Negative values located spread along the coast (east part and top north) while the positive value spread out landwards with the highest NDVI is 0.919, and the lowest 0.300 based on Landsat USGS classification (Weier and Herring, 2000). Visually the levels of greenness distinguish the mangrove health condition among three different years, wherein 2003 the condition of mangrove forest in the coastal region dominated by healthy vegetation cover showed by dark green color, while mangrove forest landwards is mixed from low to high NDVI.

In 2010, the mangrove forest NDVI in the coastal region, especially in the eastern side decreased slightly as shown in the picture with several areas spotted to transform from dark green to light green. The same thing with the area near to inland also degraded slightly, which explain the mangrove health degradation occurred, while mangrove in the northern coast increased slightly. In 2017 the mangrove forest condition both seawards and landwards dominated by dark green scattered smoothly along the coast and into land compared to the condition in 2003 and 2010, which portrayed as an increase in biomass and healthier vegetation.

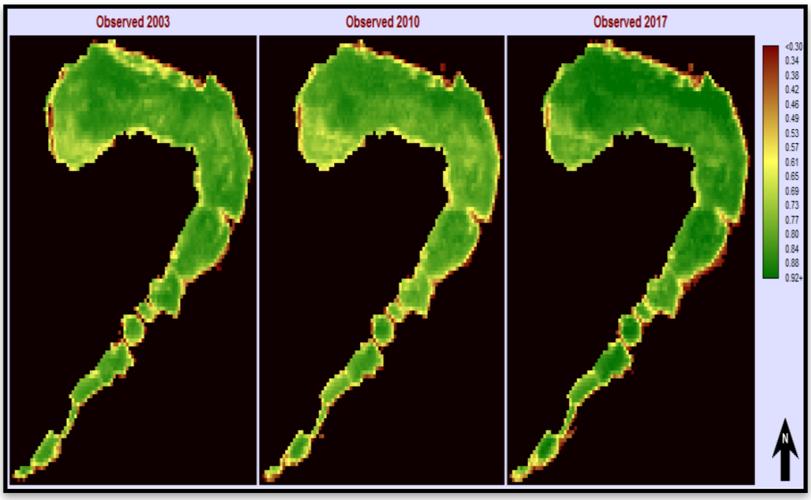

Figure 3-1: Mangrove NDVI over periods

The histogram shows the NDVI composition over periods (Figure 3-2), where the index composition in 2003 somewhat changed a little bit in 2010. Changesin NDVI ranged from 0.7 to 0.9 with most of the NDVI ranged from 0.8 to 0.9 decreased slightly to a range between 0.7 and 0.8, while the NDVI ranged from 0.3 to 0.6 remains steady. Massive changes occurred in 2017 where the NDVI ranged 0.85 to 0.9 escalated significantly in number from below 1.000 points observation to almost 1.500 points, which strengthened by the new highest NDVI above 0.9 with approximately 200 points. The condition in 2017 regarded as the mangrove health upgrade in this region derived from low to moderate and converted into high NDVI from 2010 condition.

Statistically, the mangrove forest health in 2010 was somewhat decreasing as shown by its both median and mean value with approximately 0.01 gap compared to 2003, while in 2017 the median and mean value escalate significantly by 0.6 to 0.7 respectively compared to 2010. The standard deviation of points observation in 2017 is 0.11, which are varied compared to 2003 and 2010 with around 0.10 (Table 3-1).

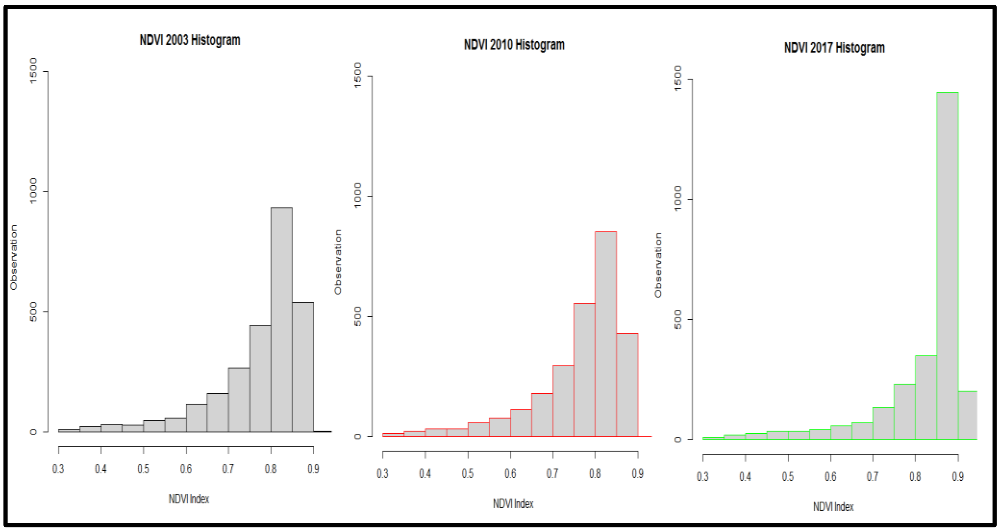

Figure 3-2: Mangrove forest condition based on the number of pixels over time frames

Table 3-1: Statistical information of NDVI index over time frames

No	Category	NDVI 2003	NDVI 2010	NDVI 2017
1	Minimum	0.302	0.311	0.305
2	Maximum	0.903	0.901	0.919
3	Median	0.809	0.796	0.867
4	Mean	0.773	0.763	0.821
5	Standard Deviation	0.106	0.106	0.110

Regression Analysis One (Figure 3-3(a)) derived from the image 2010 with 2003 resulted in a strong positive correlation between both images with R^2=0.78 (coefficient determination), which explained 78% total variation of point observation in image 2003 by the point observation in image 2010. The same methods applied for image 2010 and 2017 named Regression Analysis Two (Figure 3-3(b)) and resulted in the same firm positive correlation with R^2=0.78. Both Regression Analysis illustrates how the treatment experienced by the NDVI image 2003 influenced NDVI image in 2010, while the NDVI 2010 affecting the image in 2017.

The results of Paired T-test between two images NDVI 2003 and NDVI 2010 using two-sided tailed with confidence level 99% shows that both images are a statistically significant difference between the mean of NDVI 2003 and NDVI 2010 based on its p-value < 0.01. The same condition occurred between NDVI 2010 and NDVI 2017, which concluded the NDVI image 2003, 2010 and 2017 are statistically different.

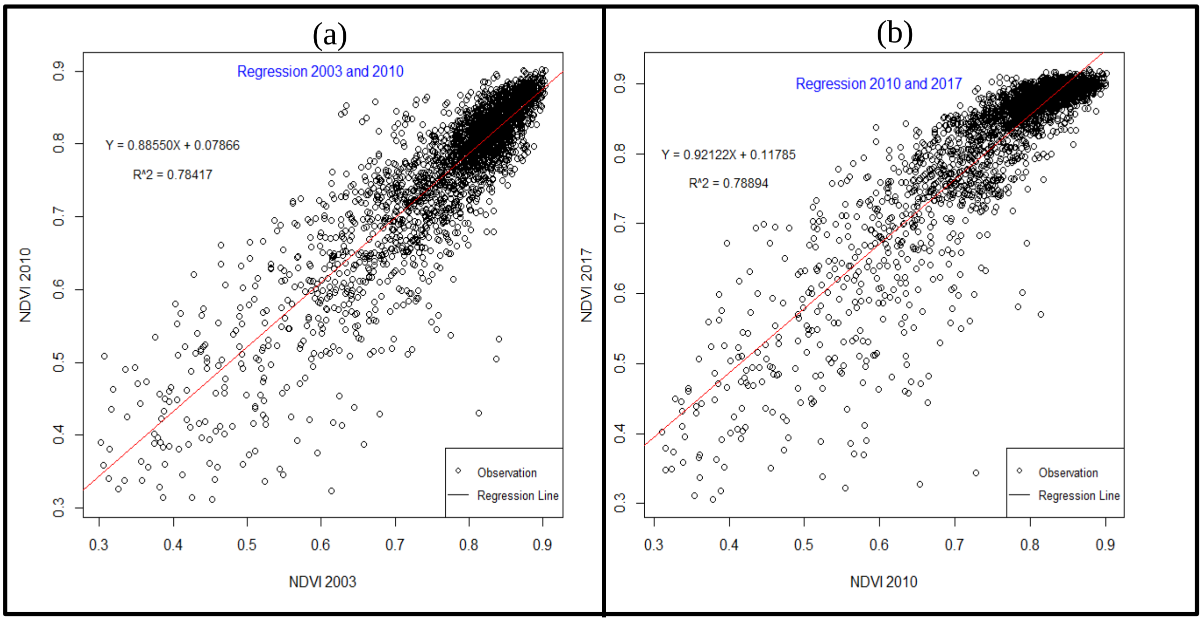

Figure 3-3: Regression between 2003 and 2010 (a) and between 2010 and 2017 (b)

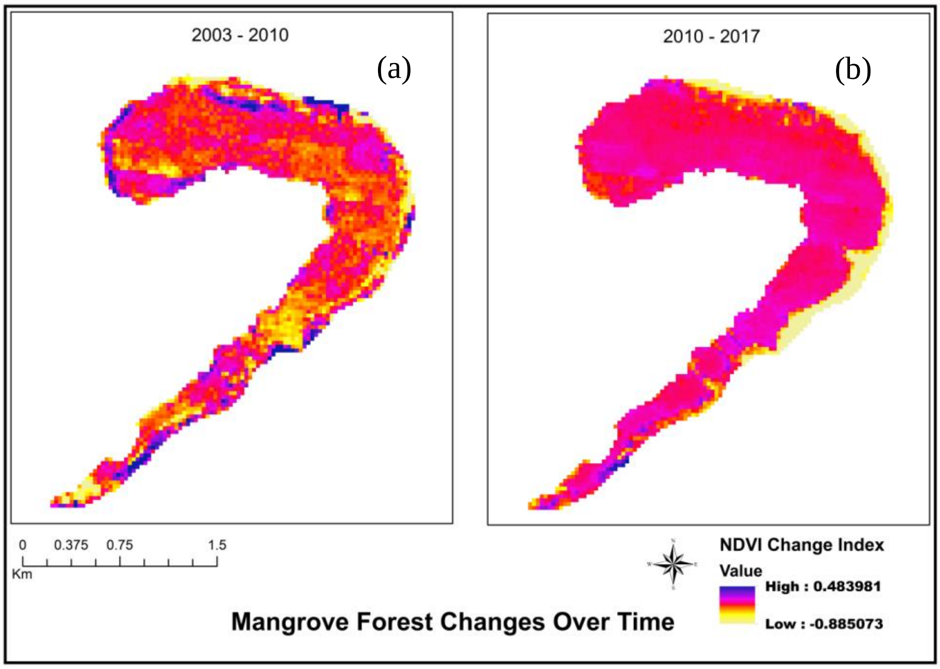

Figure 3-4: Mangrove Change 1 (a) and Mangrove Change 2 (b)

Table 3-2: Statistical information of Mangrove Change

No	Category	Mangrove Change 1	Mangrove Change 2
1	Minimum	-0.382	-0.384
2	Maximum	0.219	0.275
3	Median	-0. 010	0.058
4	Mean	-0.009	0.057
5	Standard Deviation	0.051	0.051

Mangrove forest change index over time (Figure 3-4) derived by subtracting two images resulted in mangrove change index named as Mangrove Change 1 (images 2003 and 2010, Figure 3-4(a)), and Mangrove Change 2 (images 2010 and 2017, Figure 3-4(b)). These changes index illustrates the magnitude of changes occurred within the period before the MPA designation and after the MPA designation. Blue color represents the high-positive change of NDVI mangrove forest, while yellow indicates the low-negative change of NDVI. Mangrove Change 1 consisted of mixed change index between positive and negative change, where the Mangrove Change 2 dominated by small positive changes spread along the mangrove forest area, with negative change along the east coast. From 2003 to 2010, more areas appeared to have lower growth in NDVI, while between 2010 and 2017 mostly experienced higher growth with low growth concentrated in the coastal region.

Statistically, the Mangrove Change 1 dominated by negative changes across the region shown by the median and mean value -0.010 and -0.009 respectively, while the opposite condition happened in Mangrove Change 2 where changes controlled by positive value with median 0.058 and mean 0.057. Standard deviations in Mangrove Change 1 and 2 are relatively similar with 0.051, which indicates uniform variation as shown in table 3-2.

The Mangrove Change index histogram (Figure 3-5) explains the changes in NDVI before and after MPA

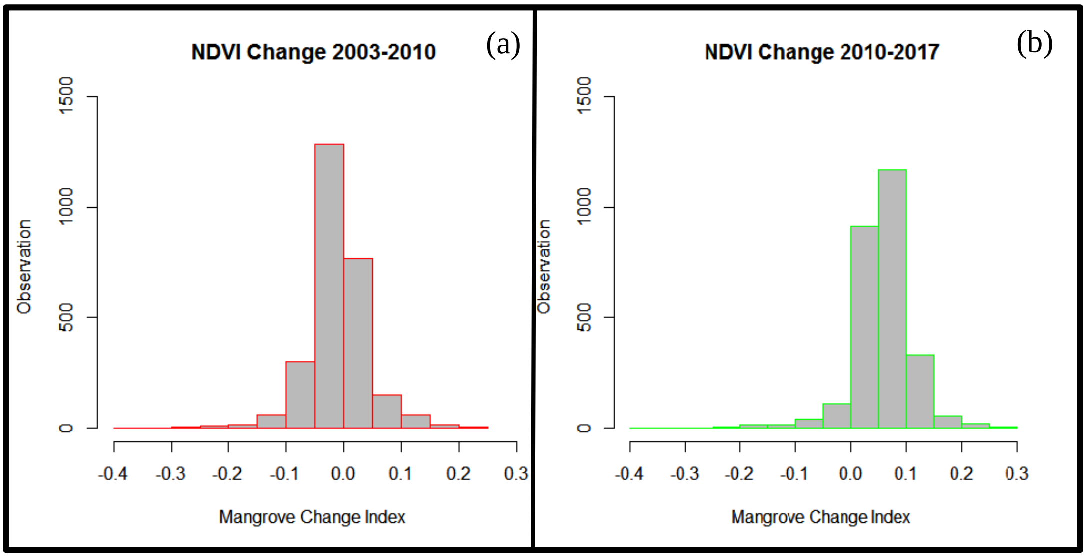

Figure 3-5: Mangrove Change 1 Index (a) and Mangrove Change 2 Index (b)

designation in Nusa Penida. Before the MPA designation (Figure 3-5(a)), the mangrove forest change dominated by negative to slightly no change, which considered as degradation condition demonstrated by numerous values ranged between -0.1 to below 0.05. While after the MPA designation (Figure 3-5(b)) its turnout to a positive value with range started from 0.05 to 0.15.

Mangrove Change Regression Analysis derived from Mangrove Change 1 and Mangrove Change 2 resulted in a regression equation model to estimate the effect of MPA on the change in mangrove NDVI per 7 years as follows:

$$Y = MPA * 0.067585 - 0.0098933 \quad (3\text{-}1)$$

Where,

Y : Change NDVI

MPA : The average effect of the MPA implementation on change in NDVI/7years

$$MPA\ Impact = Observed\ 2017 * 0.067585 - 0.0098933 \quad (3\text{-}2)$$

$$NDVI\ in\ 2017\ without\ MPA = Observed\ 2017 - 0.0098933 \quad (3\text{-}3)$$

The impact of MPA designation in Nusa Lembongan was mapped using the Mangrove Change Regression Analysis (Figure 3-6(a)), and project the condition of mangrove forest in Nusa Lembongan without MPA (Figure 3-6(b)). The NDVI impact mostly occurred almost in all mangrove forest regions, especially positive impact landwards indicated by dark green, while yellow color displayed slightly no changing effect, and red color that represents the negative impact of the MPA designation occurred along the coastal region.

The accuracy assessment using Cohen's Kappa resulted in similar Kappa coefficient (Table 3-3) between periods with average 0.71, which means that the accuracy assessment displays a good agreement between the invented random samples applied to Google Earth High-Resolution with the satellite images.

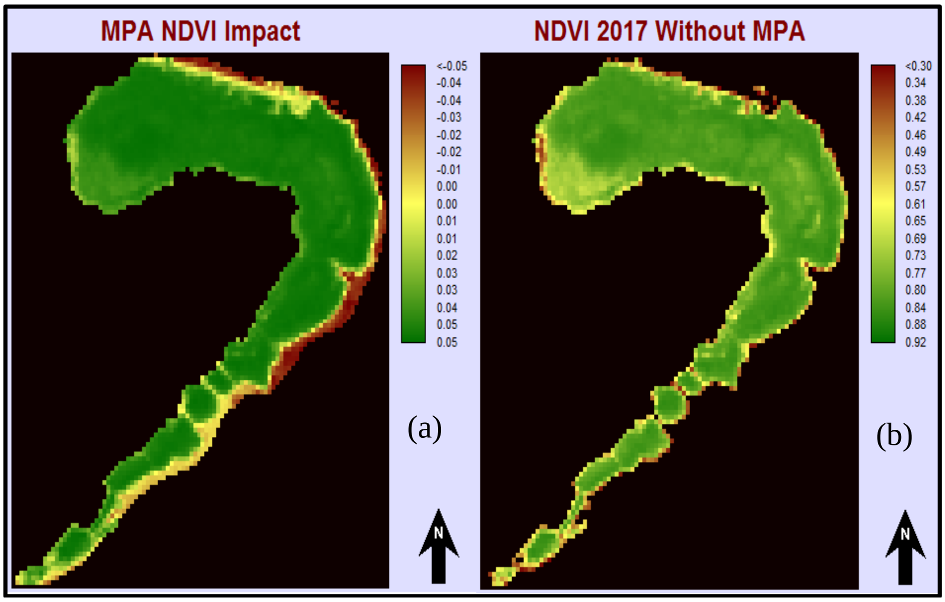

Figure 3-6: The NDVI Impact (a), and NDVI 2017 without MPA (b)

The Hotspot analysis (Figure 3-7 resulted in three different images as shown in picture above, where the blue (dark) colour illustrate the spatial distribution of low values (cold spot) based on its NDVI values, while the red (bright) colour, represent the high values (hotspot) in three confidence level 99%, 95%, and 90% (Nallan *et al.* 2015).

In 2003 the hotspot and cold-spot distributed evenly along the mangrove forest area within three different confidence level, while in 2010 the hotspot clustered in the middle of mangrove forest, which associated with the fall of NDVI in 2010. Hotspot analysis in 2017 shows the domination of high value across the region and strengthens statistics information where massive positive conversion of NDVI occurred in that year compared to the previous periods in 2010 and 2003.

Based on several images resulted from remote sensing approach, the mangrove forest condition in Nusa Penida MPA changed substantially, which influenced by the MPA implementation in 2010. The mangrove forest health, which associated with biomass vegetation in 2003 slightly decreased in 2010, and increase considerably in 2017. The condition of mangrove forest in 2003, 2010, and 2017 are significantly different based on paired t-test result (p-value < 0.01) using confidence interval 99%, where the mean difference in 2003-2010 and 2010-2017 are 0.009 and 0.057 respectively.

Table 3-3: Classification accuracy using Cohen's Kappa methods

No	Years	Accuracy (%)	Kappa Coefficient
1	2003	88.40	0.70
2	2010	88.00	0.71
3	2017	89.73	0.73
4	Average	88.71	0. 71

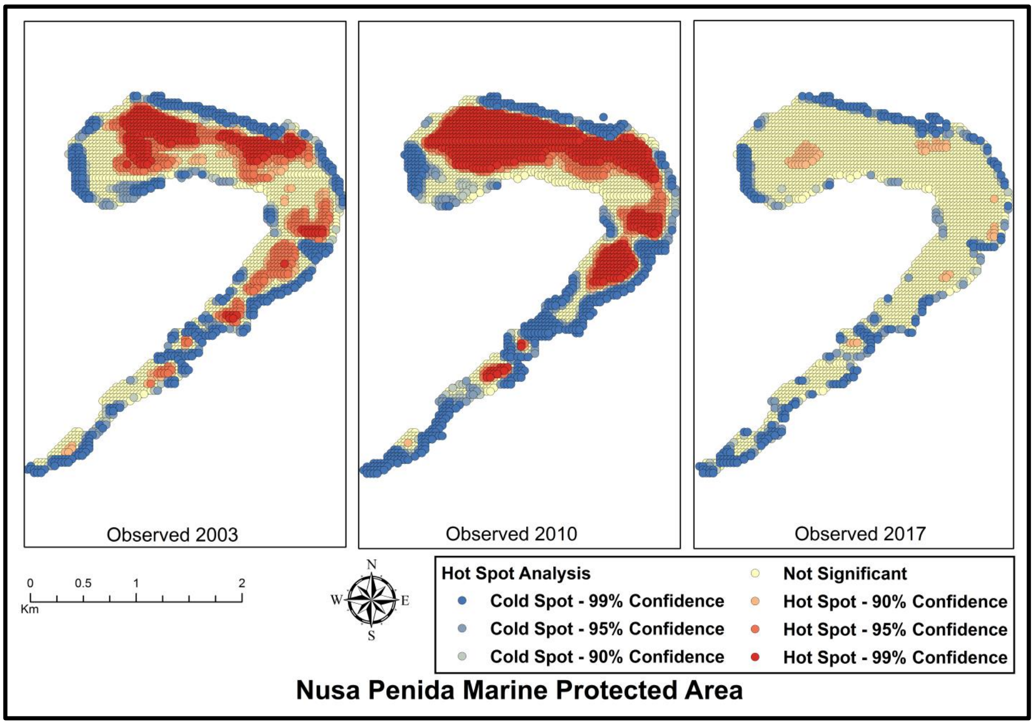

Figure 3-7: Hotspot Analysis in Nusa Penida MPA

Mostly positive change in 2010 occurred landwards (west direction), while negative change considered as mangrove degradation happened in the middle of mangrove forest towards the sea. This might happened due to tidal, wave combined with sea level rise in the region, and its location directly adjacent to Lombok Straits in the west, which famous by its strong current (Lubis and Yuningsih 2016) and internal wave (Rachmayani *et al.* 2010).

The condition of mangrove forest in 2017 experienced an upgrade evenly across the region supported by statistical analysis, hotspot analysis, and image visualization. Mangrove forest change in 2017 dominated by a small positive value in almost all mangrove area, especially in the middle (both landwards and seawards), which indicates growth during the MPA implementation. Statistics table and information through histogram strengthen the evidence. The similar condition in 2010, where mangrove forest in the coastal region suffered from nuisance derived from tidal, wave and sea level rise combination (Lovelock *et al.* 2017).

Image regression before and after the MPA implementation shows strong positive correlation explained by R^2 = 0.78, which conclude the contribution of MPA to the region where the condition before the implementation dominated by negative to slightly no change, while after the MPA implementation it is slowly turned into positive change.

4 CONCLUSION

The output of this study is relevant to environmental and conservation management in Nusa Penida MPA, primarily to mangrove forest management. The mangrove forest health decreased in quality from 2003 to 2010 before the MPA designation and increased significantly from 2010 to 2017 after the MPA designation. The MPA implementation play key role in managing, conserving and protecting the existing ecosystem with its spatial planning, zoning system, and strict regulation, but other driver natural and unnatural reasons also contributed to the changes.

Field observation needed for ground truthing to support the accuracy assessment, land use and land use change classification for better, and comprehensive analysis in the MPA implementation. Lastly, it is vital to put attention on the MPA management and implementation in Nusa Penida MPA as a role model on spatial planning included how to address several issues within stakeholder for better natural resource management in the future.

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