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Changes Detection of Mangrove Vegetation Area in Banyak Islands Marine Natural Park, Sumatra, Southeast Asia

Muhammad Arif Nasution[a], Helmy Akbar[b], Singgih Afifa Putra[c], Esraa E. Ammar[d,e], Ammar AL-Farga[f], Yudi Setiawan[b,g]

[a] Department of Aquatic Resources, Faculty of Fisheries and Marine Science, Teuku Umar University, Aceh Barat, 23615, Indonesia
[b] Center for Environmental Research, IPB University, IPB Dramaga Campus, 16680, Bogor, Indonesia
[c] Center for Quality Assurance Development of Vocational Education in Maritime, Fisheries, Information and Communication Technology (BPPMPV KPTK), Makassar, 92171, Indonesia
[d] Plant Ecology, Botany Department, Faculty of Science, Tanta University, Gharbia, 31527, Egypt
[e] School of Food and Biological Engineering, Jiangsu University, Zhenjiang, 212013, China
[f] Department of Biochemistry, Faculty of Science University of Jeddah, Jeddah, 23218, Saudi Arabia
[g] Conservation of Forest Resources and Ecotourism, Faculty of Forestry and Environment, IPB University, IPB Dramaga Campus, 16680, Bogor, Indonesia

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ABSTRACT

The mangrove ecosystem in the Banyak Islands faces urgent challenges due to environmental pressures, highlighting the need for accurate identification and conservation efforts. Mangrove forests provide crucial ecological benefits, making their preservation vital for sustainable regional development. To address these challenges, this study analyzed changes in mangrove vegetation on Tuangku Island, part of the Banyak Islands Marine Natural Park (BIMNP), over a decade (2010–2020). The methodology utilized Landsat imagery and ALOS PALSAR data, which were analyzed through the Google Earth Engine platform. Spectral index combinations, including NDVI, NDMI, MNDWI, and MVI, were analyzed using random forest classification, a tree-based machine learning algorithm. The study's methodology revealed that the total estimated mangrove area was 818.21 hectares in 2010, increased to 939.91 hectares in 2015, and then slightly decreased to 899.96 hectares in 2020. These findings indicate an initial expansion of mangrove vegetation followed by a decline, suggesting fluctuating environmental conditions or human impact over the period studied. The findings highlight the critical need for continuous monitoring and adaptive management practices to support the long-term sustainability of the mangrove ecosystem within the BIMNP. Based on these findings, we recommend implementing targeted conservation measures and further research to understand the underlying causes of the observed changes, thereby supporting the region's sustainable development and ecological health.

Introduction

Mangrove forests represent highly diverse ecosystems occupying tidal zones within equatorial and warm-temperate latitudes, approximately ranging between 30 °N and 30 °S [1,2]. Mangrove forests offer a range of ecosystem services, including serving as nurseries for various marine fishery species, trapping sediments, enhancing coastal stability, supporting biodiversity, sequestering carbon, and promoting ecotourism [2–5]. Due to decreased forest cover and ecological degradation, mangrove forests are one of the most carbon-rich sources in tropical regions, making them a crucial area for conservation. Mangrove forests are potential targets for conservation initiatives under the Reduce Emissions from Deforestation and Degradation (REDD+) program [6,7].

Corresponding Author: Muhammad Arif Nasution arifnasution@utu.ac.id Department of Aquatic Resources, Faculty of Fisheries and Marine Science, Teuku Umar University, Aceh, Indonesia.

This ecosystem is considered among the most fragile on the planet due to human-induced disturbances and climate change impacts, such as pollution, escalating sea levels, and land-use changes. Earlier studies indicate that deforestation has resulted in the loss of 20% to 35% of the global mangrove forest area since the 1980 [4,8,9]. Many studies have shown that mangrove land changes result in the degradation and species loss of important communities [10,11]. The phenomenon of mangrove forest degradation has attracted coastal managers and researchers to monitor the ecological aspects of this habitat, including spatial and temporal changes. Numerous monitoring initiatives have been conducted, spanning from regional to global levels [2,7,12–15].

Banyak Islands Marine Natural Park (BIMNP) acts as a marine protected area situated in the western part of Sumatra, Indonesia, covering approximately 255,585.39 hectares, with sea regions encompassing about 228,182.86 hectares (89.3% of the area) and land cover accounting for around 27,402.53 hectares (Minister of Forestry and Environment decree No. 103/MenLHK-II/2015 amandement decree No. 86/Menhut-II/2014 rearding forest area and waters conservation of Aceh Province). The dominant coastal ecosystem in this area, particularly Tuangku Island, is mangrove forests. Additionally, the region harbors other vital ecosystems, such as coral reefs and seagrass beds [16–18]. BIMNP has garnered attention from investors looking to develop the tourism industry because of the islands' biodiversity and unique habitats [19]. However, there is currently no available data on the extent of mangrove forests in this region. The development of the tourism industry is poised to impact the existence of coastal ecosystems in BIMNP, particularly mangrove forest ecosystems. Therefore, this study aimed to survey the mangrove forests in the Banyak Islands Marine Natural Park, Sumatra, both spatially and temporally. This study serves as a crucial step towards sustainable development of the tourism industry in this area.

Materials and Methods

Data Source

This study was performed in the eastern part of Tuangku Island (2°10'50,000"" N, 97°16'16,000"" E, < 30m above sea level) (Figure 1). Tuangku Island is the largest island, covering ± 11,500 ha (10.7% of the area) in the BIMNP. Multi-temporal satellite imagery was utilized to analyze changes in mangrove forests over the period from 2010 to 2020. Satellite images were obtained from Landsat 7, Landsat 8, and the Global PALSAR-2/PALSAR Yearly Mosaic (Table 1). The correction of cloud and shadow cover was eliminated using top-of-atmosphere (TOA) reflectance by correction level with Algorithm Fmask and Cmask from the Google Earth Engine [20].

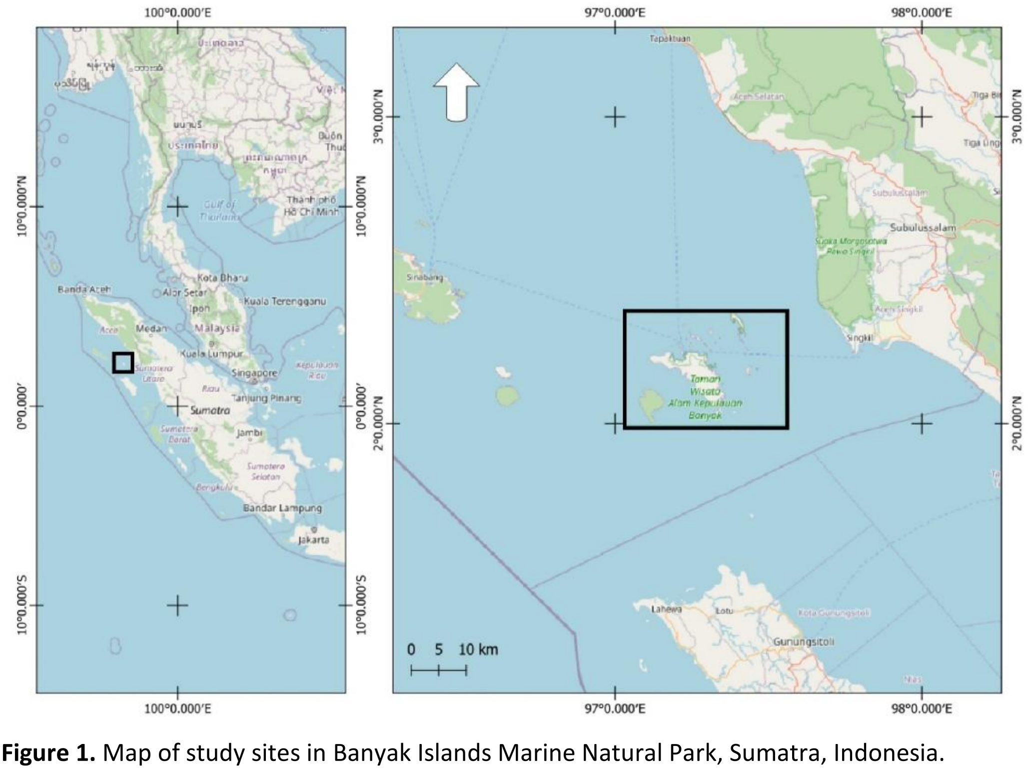

Figure 1. Map of study sites in Banyak Islands Marine Natural Park, Sumatra, Indonesia.

Table 1. Satellite imagery properties used in this study.

No.	Attributes	Satellite imagery	Year	Resolution	References
1	B3, B4, B5, B6, & B7	USGS Landsat 8 Surface Reflectance Tier 1	2015 and 2020	30 m	USGS
2	B2, B3, B4, B5, & B7	USGS Landsat 7 Surface Reflectance Tier 1	2010	30 m	USGS
3	HH & HV	Global PALSAR-2/PALSAR Yearly Mosaic	2010, 2015 and 2020	25 m	[21]
4	Elevation	NASA SRTM Digital Elevation 30m	2000	30 m	[22]
5	Mangrove	GMW 2010-2016_v2	2010-2016	30 m	[23]
6	R, G, B, & NIR	Planet-nicfi/assets/basemaps/asia	2015	4.77 m	[24]

Data Processing

Landsat 7 and 8 imagery data were utilized to identify alterations in mangrove vegetation area on Tuangku Island over a five-year interval (2010–2020). PALSAR-2/PALSAR satellite imagery was also used to estimate the temporal changes in mangrove vegetation. Satellite image data processing tool using Google Earth Engine (GEE).

Landsat 8 and 7

Data processing begins with importing data, determination of the areas of interest, tabulation of satellite imagery by date, and elimination of shadow and cloud cover [20] (Table 1). Spectral index input, determination of elevation limits, digitization of mangrove and non-mangrove vegetation data samples, building used models, training data samples and predictors, running models, validation, and estimation of the area of mangrove vegetation were performed [25]. The spectral index combination was estimated as the NDVI (Normalized Difference Vegetation Index) [26], NDMI (Normalized Difference Mangrove Index) [27], MNDWI (Modified Normalized Difference Water Index) [28], and MVI (Mangrove Vegetation Index) [29]. Spectral index data were processed using a tree-based Machine Learning Algorithm for random forest classification.

The decision tree (decision-making tree) was used as a suitable random forest method [30]. The random forest classification algorithm constructs decision trees for each predictor sample to distinguish mangrove from non-mangrove vegetation utilizing pixel-based spectral indices. This study employed 100 decision trees and five predictors, with sample data from 2010 (1,163 points), 2015 (639 points), and 2020 (677 points). The dataset was split into 70% for training and 30% for testing. The classifier's accuracy was evaluated using a Confusion Matrix and kappa statistic.

ALOS PALSAR

The Processing of ALOS PALSAR data was based on the GEE platform by combining the ALOS PALSAR mosaic image sets from 2010, 2015, and 2020. The Japanese Aerospace Exploration Agency (JAXA) compiled and provided the data. The image composite was visually analyzed to identify the spatial distribution of changes in extent over the period from 2010 to 2020, assessed at five-year intervals. Change validation refers to the temporal and spatial information on Landsat satellite imagery from 2010 to 2020 using the GEE platform.

ALOS PALSAR satellite imagery data were collected through the GEE dataset, followed by color composite (2010, 2015, and 2020 in red, green, and blue) [23], a polarizing channel in HV. Each color composite signifies a specific time (red: 2010, green: 2015, and blue: 2020). The composite blend of colors describes the changes in the mangrove vegetation area over time. The decline in backscatter in 2010 indicated the loss of mangrove vegetation. This can be observed in the red areas owing to the relatively high backscatter in 2015 and 2020. In contrast, the blue area resulted from the increase in backscatter since 2015, which indicates the expansion of mangrove vegetation areas on the coastline.

Results and Discussion

Mangrove Vegetation Area

According to Landsat data processing, the estimated mangrove area 2010 was 818.21 ha (Figure 2a). In 2015, it covered 939.91 ha (Figure 2b); in 2020, it covered 899.96 ha (Figure 2c). There was an increased area of mangrove vegetation from 2010 to 2015, covering 121.7 ha (14.81%), while from 2015 to 2020, there was a decrease of approximately 39.95 ha (4.25 %). Research conducted by Bunting et al. [31] also showed that mangrove cover increased by 13% between 2010 and 2015 on Tuangku Island (Table 2).

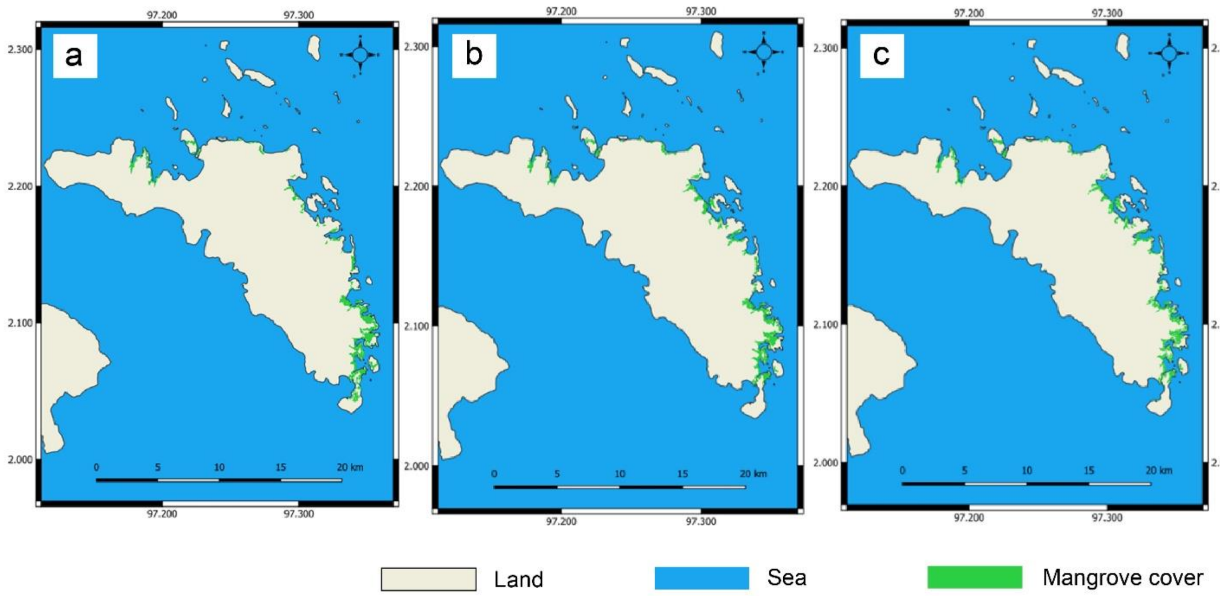

Figure 2. Map of mangrove vegetation areas of Tuangku Island based on satellite imagery, a) 2010, b) 2015, c) 2020.

Table 2. Determination of accuracy.

Year	Overall accuracy (%)	Kappa
2010	97	0.95
2015	96	0.93
2020	100	1

The kappa values were categorized into different groups. If kappa is less than zero, then the results are unacceptable; 0–0.20 is called less acceptable; 0.21–0.40 is represented as quite acceptable; 0.41–0.60 is considered feasible, 0.61–0.80 is considered substantial, and 0.81–1.00 is considered highly acceptable [23,32–34]. Our results illustrate that most images were classified, generally having a high overall accuracy level (> 95.0%). Particularly in 2020, the result has an overall accuracy of 100%, and the kappa statistics range from 0.90 to 1. Subsequently, the classification of the data was acceptable.

Landsat imagery enabled the mapping of mangrove cover at a spatial resolution of 30 meters. Comparable research utilizing Landsat 8 OLI has been carried out in the Sundarbans Delta as well as in regions of West and Central Africa. The results displayed an overall accuracy of 84.1% with a kappa coefficient of 0.74 [33]. In a different study, the spatial distribution of mangrove areas in the Philippines in 2000 was mapped using Landsat images [35].

Spatial and Temporal Dynamics of Mangrove Area

Changes in the detection of mangrove vegetation areas on Tuangku Island, either elevation or dropping over the last decade (between 2010 and 2020), according to ALOS PALSAR imagery data processing (Table 3). From 2010 to 2015, there was an elevation of the mangrove vegetation area of about 145.39 ha, while from 2015 through 2020, there was a depression of the mangrove cover of about 40.21 ha. The estimation areas of mangrove vegetation processed using ALOS PALSAR and Landsat data were different because of the limitations of the satellite sensors. The presence of cloud cover and shadows is a limitation of Landsat satellite imagery, whereas the ALOS PALSAR satellite imagery cannot distinguish between mangrove and non-mangrove areas. Data from ALOS PALSAR imagery can describe mangrove areas with more than 90% accuracy in almost all iterations [36]. It is possible to link natural processes, mostly from erosion (Figure 3) rather than human activity, to the dynamics of changes in the Tuangku Island mangrove habitats.

Table 3. A decade changes in mangrove vegetation area in Tuangku Island period 2010–2020.

Parameter	2010–2015	2015–2020
Occurrence (ha)	288.08	169.68
Loss (ha)	142.69	209.89

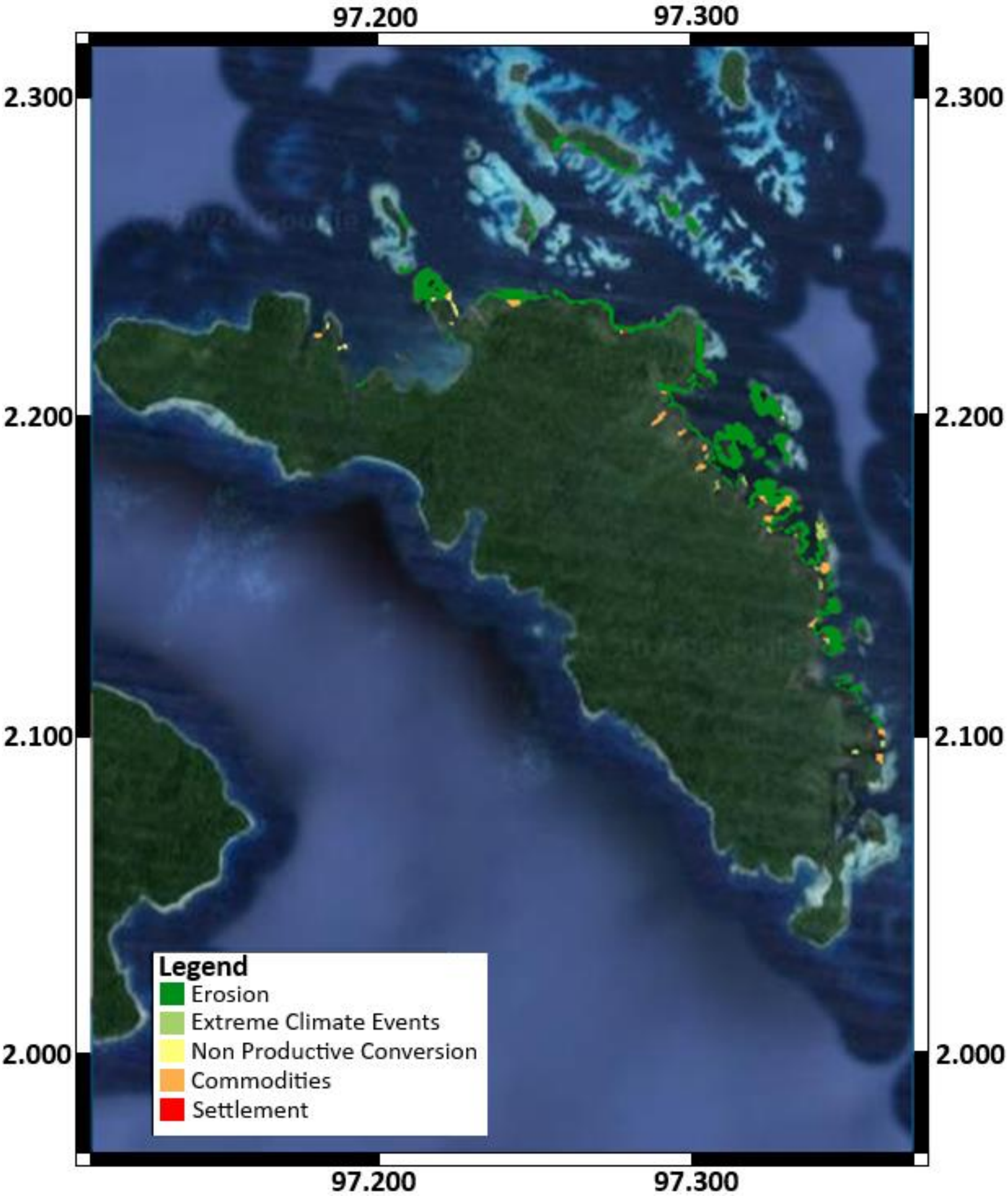

Figure 3. Map of mangrove lost driver on Tuangku Island from 2000–2016, extract from Goldberg et al. [35].

Comparison with Existing Maps

Accurately identifying mangrove vegetation areas on a regional scale is difficult, particularly in regions with different densities of mangrove vegetation. Although mangrove vegetation covers a small area of the Earth's surface, visual analysis has been extensively employed to map mangrove vegetation and enhance map accuracy [2,31,37–41]. Previous study has been mapping mangrove areas globally, a method was devised using an Extremely Randomized Trees classifier to analyze ALOS PALSAR satellite imagery and Landsat sensor data, achieving an accuracy level of 93.6–94.5% [42] (see Figure 4a). According to the comparative results of the spectral index and combination results in 2015, there was a considerable difference (> 40%) (Figure 4b). On a regional scale, the estimation error by Bunting et al. [31] is relatively clear. Visual comparison indicates that the estimation of mangrove vegetation area in previous studies [31,42], is significantly larger than the actual extent. Figure 4c presents mangrove detection from GMW v3 [42], which overestimates the vegetation area due to limitations in spectral resolution. Figure 4e shows mangrove detection using GMW15_v2 [31], where further overclassification exacerbates the discrepancies. This overestimation was also confirmed using satellite imagery NICFI from 2015 (Figure 4d).

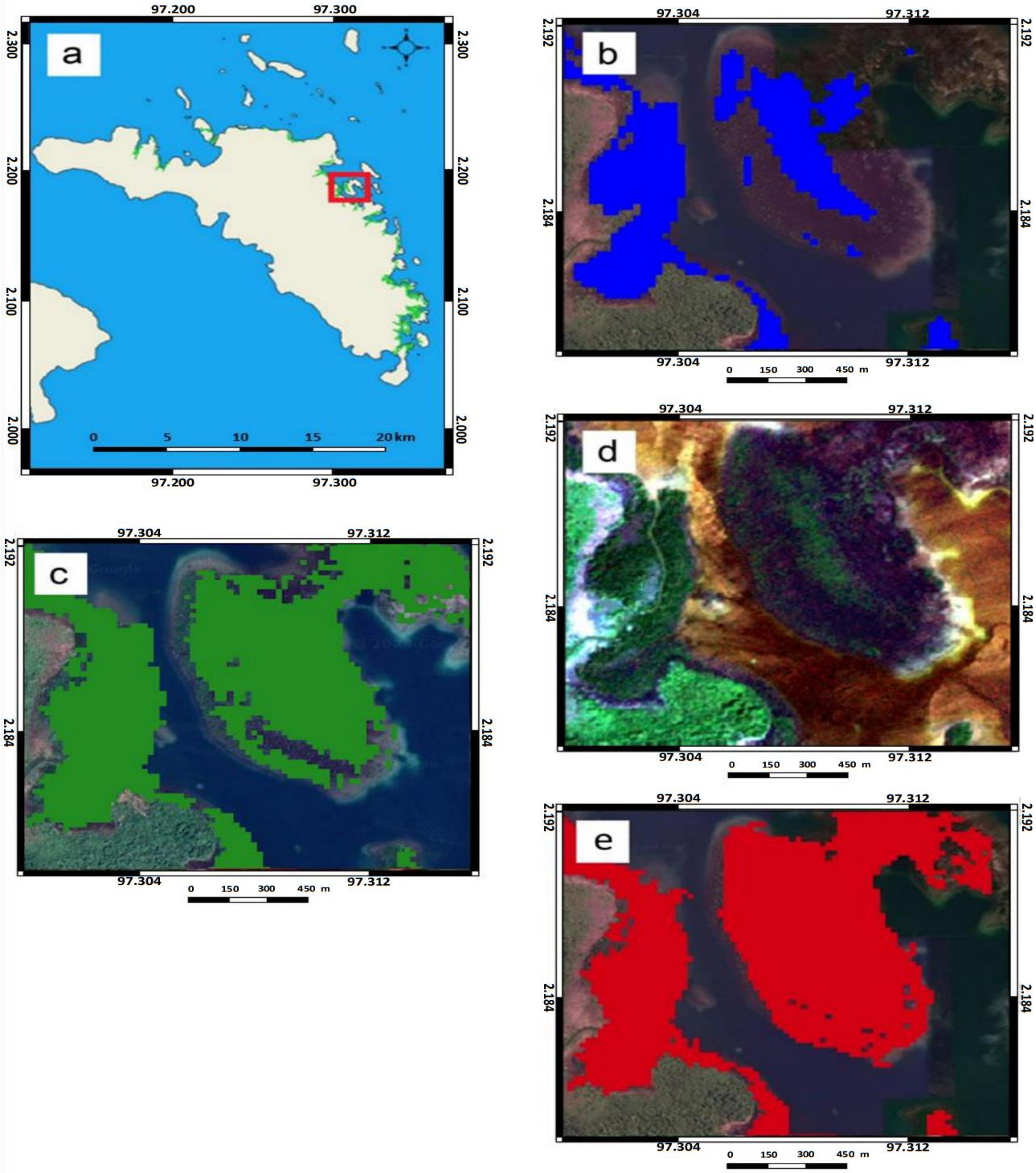

Figure 4. Comparison of change detection in mangrove vegetation, a. Locator map of the Tuangku Island mangrove vegetation in 2015; b. Mangrove vegetation area was detected using a spectral index combination in this research; c. Mangrove detection from GMW v3 [42]; d. Satellite imagery PlanetNICFI 2015 (4.77 m/pix simple ratio R: min 20, max 411; G: min 95); e. Mangrove detection using GMW15_v2 [31].

Conclusions

It is concluded that there is an obvious change in the mangrove vegetation from 2010 to 2015 in Tuangku Island, covering an area of 121.7 hectares (Landsat imagery) and 145.39 hectares (ALOS PALSAR imagery). A clear decrease in mangrove vegetation from 2015 to 2020 in Tuangku Island was recorded, covering an area of 39.95 hectares (Landsat imagery) and 40.21 hectares (ALOS PALSAR imagery). The results of this study can aid in the management of the Banyak Islands Marine Natural Park in the planning of regional sustainable development.

Author Contributions

MAN: conceptualization, methodology, formal analysis, & drafting; **HA:** data curation, review and editing, and visualization; **SAP:** investigation, provided resources, & draft preparation; **EEA:** validation, formal analysis, and reviewing, & editing; **AA-F:** supervision, reviewing, & editing; **YS:** conceptualization, methodology, supervision, project administration, review & editing.

Conflicts of interest

The authors declare that the research was conducted without any commercial or financial relationships that could be construed as potential conflicts of interest.

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