RESEARCH ARTICLE

MEDIA KONSERVASI
SCIENTIFIC JOURNAL IN CONSERVATION OF NATURAL RESOURCES AND ENVIRONMENT

Dynamic Change of Mangroves in Aceh Tamiang Regency using Landsat Temporal Data, 2000 to 2023

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Article Info:
Received 19 May 2024
Revised 30 April 2025
Accepted 30 April 2025

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Abstract

Mangroves, known for their high productivity, play vital roles in physical, ecological, and economic aspects that benefit human life. However, these ecosystems are currently threatened by climate change and human activities. To address this challenge, Indonesia aims to rehabilitate 600,000 hectares of mangroves by 2024. Effectively monitoring changes in mangrove dynamics is crucial for achieving this goal. This study focuses on understanding the dynamic change of the mangrove land cover in Aceh Tamiang from 2000 to 2023. Mangrove dynamics in Aceh Tamiang are important because it has the largest mangrove area in East Aceh, which is decreasing due to conversion to the oil palm industry. The classification using random forest (RF) algorithm by utilizing VWB-IC (Vegetation-Water-Built-up Index Combined), which area NDVI, SAVI, ARVI, GNDVI, SLAVI, and EVI as vegetation indices; MNDWI and ANDWI as water indices; and NDBI as built-up index. The employment of this combination is necessary to enhance the accuracy of classification due to the addition of more input parameters to machine learning. The image data are acquired through Landsat 5 for 2000 and 8 and 9 satellites for 2023. The observed dynamics include mangroves transitioning into fishponds (768 ha) and plantations (2,679 ha) between 2000 and 2023. The processed data indicates a decrease in the Aceh Tamiaang mangrove area from 13,270 ha in 2000 to 9,386 ha in 2023. These results can be used to determine mangrove rehabilitation policies in Aceh Tamiang, Indonesia.

Keywords: Mangrove dynamics change, Random forest, Spatiotemporal

1. Introduction

Mangroves consisting of various groups of ground ferns, herbs, shrubs, palms, and trees growing in the intertidal zone along tropical and subtropical coastlines act as one of the most productive ecosystems [1–3]. The complex canopy morphology and robust interconnected root system in the mangrove ecosystem support its physical function as a buffer zone that maintains the stability of the coastline from tidal waves, cyclones, and high tides and minimizes the impact of natural disasters such as tsunamis [4,5]. The root structure of mangrove vegetation serves as a habitat for various marine organisms, providing breeding grounds, shelter, nesting sites, and feeding areas [6,7]. Mangroves store carbon stocks in above-ground biomass carbon, below-ground root biomass carbon, and soil sediment carbon, making them four times larger carbon stores compared to various other types of terrestrial forests [8,9]. As for the economic sector, mangrove forests can be used directly for forest products in the form of wood for firewood, charcoal, construction, furniture, and fishing tools, as well as the use of non-timber forest products in the form of fishing nets, natural clothing dyes, animal feed, organic fertilizer, medicines, food, nipa roofing, honey, and drinks [10–15]. Currently, mangroves are very vulnerable to climate change and human activities [16–18]. Every year, mangrove areas experience a decrease in area; during the

2000-2020 period, the world's mangrove area experienced a decrease in area of 284 thousand hectares, with Asia being the region that experienced the most significant loss of mangrove area [17–19]. Indonesia, the country with the largest mangrove area in the world, is estimated to have a mangrove deforestation rate of 18,209 Ha/year (2009-2019 period) [20,21]. The main drivers of global mangrove loss during 2000-2020 are anthropogenic factors, contributing 72.1%, including aquaculture development, land conversion to agriculture, and infrastructure development [22,23].

In 2024, the Indonesian government plans a very ambitious target for mangrove rehabilitation, namely 600,000 Ha [20]. Efforts that need to be made to achieve this target are paying attention to the sustainable management of mangrove forests [21,23]. A critical aspect in determining sustainable mangrove forest management policies is monitoring changes in mangrove areas [21,24,25]. Effective monitoring is done using a remote sensing approach [25]. Remote sensing spatiotemporal monitoring can provide valuable data for experts involved in determining policies at a low cost, easy to repeat, fast, accurate, and wide-scale compared to field measurements [25,26]. Several studies have been carried out related to spatiotemporal monitoring of the dynamics of mangrove changes in Indonesia, starting from Junianto [27], Irawan [28], Aritonang [29], Febrianto [30], Febriandi [31], Haikal [32], Raynaldo [33], until Ramandalush [34].However, these studies do not show in detail the dynamics of changes that occur in mangrove areas, to be precise, they do not clearly show what areas of lost mangroves have changed into. Meanwhile, research on mapping the dynamics of mangrove changes in Aceh Tamiang is still minimal; monitoring research based on remote sensing has yet to be found In addition, over the past two decades, mangrove ecosystems around the world have undergone many changes, mainly due to climate change and anthropogenic factors [16,35]. Therefore, it is crucial to conduct this research to provide data on the dynamics of change in mangrove areas, especially Aceh Tamiang, over the past two decades, whose sustainability is already threatened by human activities [36]. This research is useful in revealing detailed information on the loss or increase of mangrove areas in Aceh Tamiang Regency, ranging from the severity to the factors that cause changes.

2. Materials and Methods

2.1. Study area

Administratively, the research location was in Aceh Tamiang Regency, Aceh Province. Meanwhile, geographically, the research location was at geographic coordinates 03° 53' 18.81″ – 04° 32' 56.76″ North Latitude and 97° 43' 41.51″ – 8° 14' 45.41″ East Longitude. The research location bordered East Aceh Regency and Langsa City in the north; in the west, it bordered East Aceh Regency and Southeast Aceh Regency; in the east, it bordered North Sumatra Province; and in the south, it bordered Gayo Lues Regency (Figure 1). The data used were from 2000 and 2023, a period chosen to capture significant changes and trends.

Figure 1. Map of the study area, located between Langsa City, East Aceh Regency, and Langkat Regency.

2.2. Research flow

The research began with taking spatial data from Landsat 5, 8, and 9 satellites. Next, the data underwent a preprocessing stage in setting the time for 2000 and 2023, applying cloud masking techniques to clear the data, and cutting the focus of the research area or creating an area of interest (AoI). The modified spatial data is taken in part to create a dataset. The dataset consisted of training data and validation data. Training data was used in the random forest method. The results of the random forest algorithm operation were tested using validation data. This process was successful using the Google Earth Engine platform. Furthermore, the research was carried out using ArcMap software to map the classification data so that interpretation and assessment of changes in mangrove dynamics could be carried out. A more detailed research flow can be seen in Figure 2.

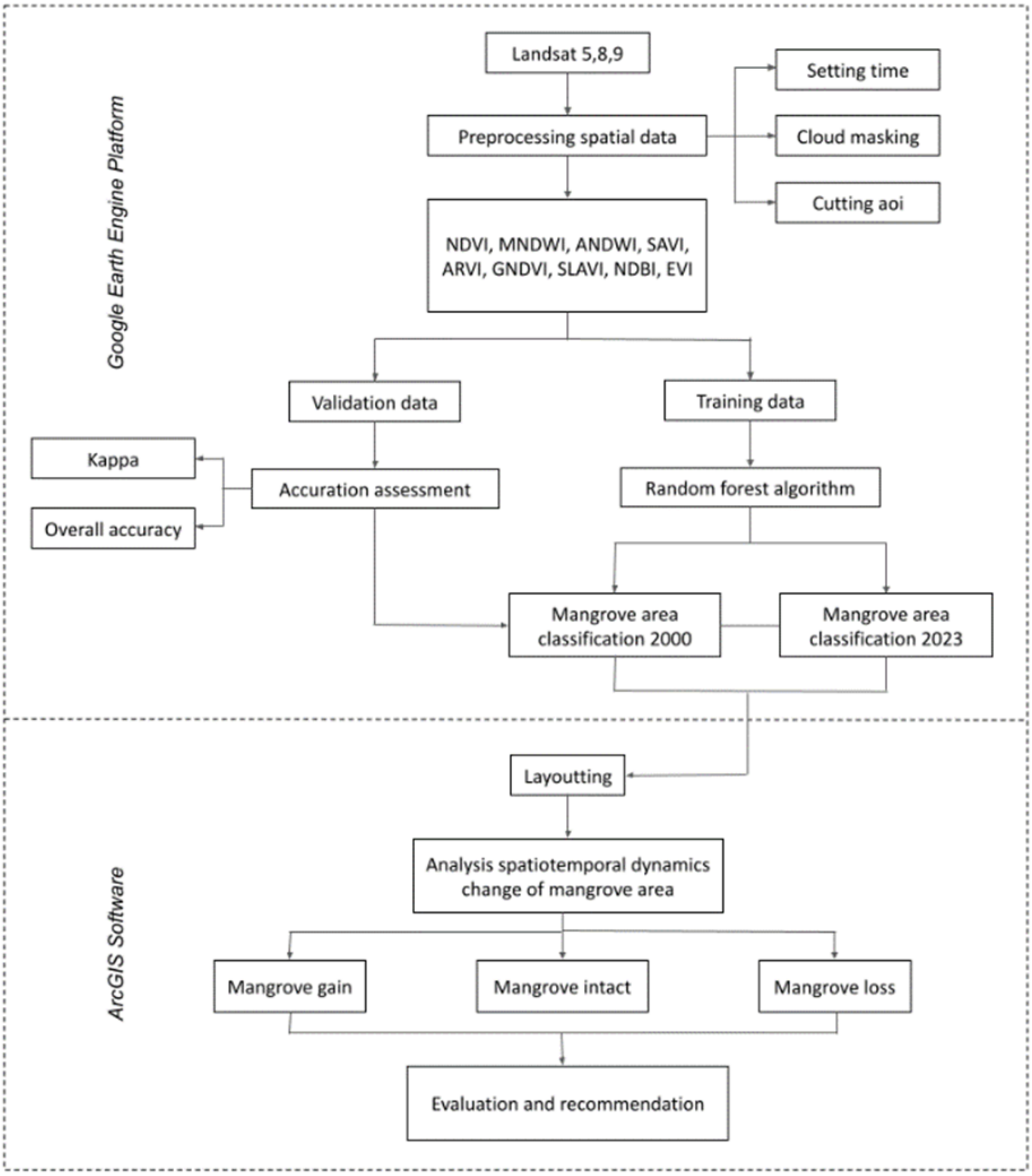

Figure 2. Research flowchart from data collection up to the suggestion.

2.3. Data

The data used in this research are spatial data obtained using remote sensing methods. Spatial data is information about a particular location on the earth's surface, including coordinates and the shape of geographic features in the form of the earth's shape [37]. The dataset that has been obtained was then processed using the land cover classification method. The classification process involved creating a dataset taken from spatial data in the form of training data and validation data. Training data is reference data for the random forest algorithm (the classification method used in this study) as teaching material that trains the random forest algorithm in predicting land cover types in the study area [38]. Generally, the more training data samples used, the better the performance of the classification algorithm [39–42]. However, the random forest method does not require massive data, it is proven that changing the training data sample size does not significantly affect the performance of the random forest algorithm [42–44]. Another dataset used is validation data which is useful for evaluating the work results of the random forest algorithm so that it can assess the accuracy of the algorithm [38,45]. The number of datasets used can be seen in Table 1.

Table 1. The amount of training and validation data used in the classification using machine learning for each type of land cover; In 2000, no training or validation data was used for the agroforestry or built-up area land cover types because in that year neither land cover was found in the study area.

No.	Variable (land use type)	2000		2023	
		training sample	validation	training sample	validation
	Water body	1165	1717	674	371
	Mangrove	1192	1726	627	36
	Plantation	923	241	617	198
	Agriculture	363	398	454	56
	Bare land	1197	736	6	184
	Agroforestry	-	-	29	81
	Built-up area	-	-	51	55

The spatial data this research uses comes from Landsat 5 satellite imagery for data needs in 2000 and Landsat 8 and 9 for 2023. The Landsat satellite is a remote sensing satellite with the first systematic collection of images of the Earth's appearance in the world launched by NASA (National Aeronautics and Space Administration) [46]. Landsat measures the reflection of light waves from objects on the earth's surface from 1972 until now, so that the resulting image data can be used to map changes in the earth's surface for specific periods. For 51 years, eight Landsat series launch missions have been successful and continue to improve with each launch. In this research, the Landsat satellite series used was Landsat 5, launched on March 1, 1984, equipped with 7 TM and 4 MSS spectral bands [47]. The consideration for using Landsat 5 for data analysis in 2000 was because it could provide cloud-free image data and was operational in 2000. Another series of Landsat satellites used in this research were Landsat 8 and 9. Landsat 8 was launched on February 11, 2013, and it consists of two instruments, namely the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) [48]. OLI is an instrument with four mirror telescopes useful for collecting invisible, near-infrared, shortwave infrared wavelength regions, and panchromatic band data. It is equipped with Quality Assurance, which detects the presence of terrain shadowing, data artifacts, and clouds [48,49]. The TIRS instrument is the newest heat sensor with a 100-m spatial resolution to reduce the number of cross-track pixels needed in applications [50]. Landsat 9 was launched on September 27, 2021, with an improved nine-band OLI-2 and two spectral band TIRS-2 instrument, which has satellite transmit data with higher radiometric resolution to increase sensitivity in detecting subtle changes [51]. The Landsat image bands used in this research are described in Table 2.

Table 2. Characteristics of the landsat-5 band used in the research [52].

Satellite	Band Number	Band Number - Band Description	Wavelength Range (nm)	Resolution (m)
Landsat 5 TM	B2	Visible Green	520 – 600	30
	B3	Visible Red	630 – 690	30
	B4	Near-Infrared (NIR)	760 – 900	30
	B5	Shortwave Infrared (SWIR) 1	1550 – 1750	30
	B6	Thermal	10400 – 12500	120 * (30)
	B7	Shortwave Infrared (SWIR) 2	2080 – 2350	30
Landsat 8 Landsat 9 OLI	B2	Visible Blue	452 – 512	30
	B3	Visible Green	533 – 590	30
	B4	Visible Red	636 – 673	30
	B5	Near-Infrared (NIR)	851 – 879	30
	B6	Shortwave Infrared (SWIR) 1	1566 – 1651	30
	B7	Shortwave Infrared (SWIR) 2	2107 – 2294	30

2.4. Data analysis

This research was carried out by analyzing the spatiotemporal dataset of mangrove change dynamics using the Google Earth Engine (GEE) cloud computing-based Application Programming Interface (API) (Figure 2). GEE is a geospatial platform that provides access to geospatial databases that reach a global scale based on Google storage and facilitates tools to process this data through coding [53–55]. GEE enables the use of climate, temperature, and geospatial model data obtained from Landsat, Sentinel, and MODIS satellites on a large scale (petabytes) [53,56,57]. This research was conducted using the Javascript programming language to run the random forest classification algorithm using a combination of various indices. The combination used is VWB-IC (Vegetation-Water-Built-up Index Combined), which consists of NDVI, SAVI, ARVI, GNDVI, SLAVI, and EVI as vegetation indices; MNDWI and ANDWI as water indices; and NDBI as built-up index. This combination of indices helps the algorithm in learning the spectral characteristics of the land cover well, so that it can better interpret the overall land cover. The random forest algorithm is a non-parametric supervised classification and regression tree (CART) method with a working mechanism in the form of multiple decision tree ensemble treatment of a randomly selected subset of training data [58,59]. The random forest classification algorithm was chosen in this research because it has been proven in many studies to be able to outperform the Binary Hierarchical Classifier (BHC), Linear Discriminant Analysis (LDA), Artificial Neural Network (ANN) classifiers, and decision tree classifiers [58]. Random forest can process multidimensional data better than other methods with fewer parameter settings, and its performance is faster compared to support vector machines (SVM) [60,61].

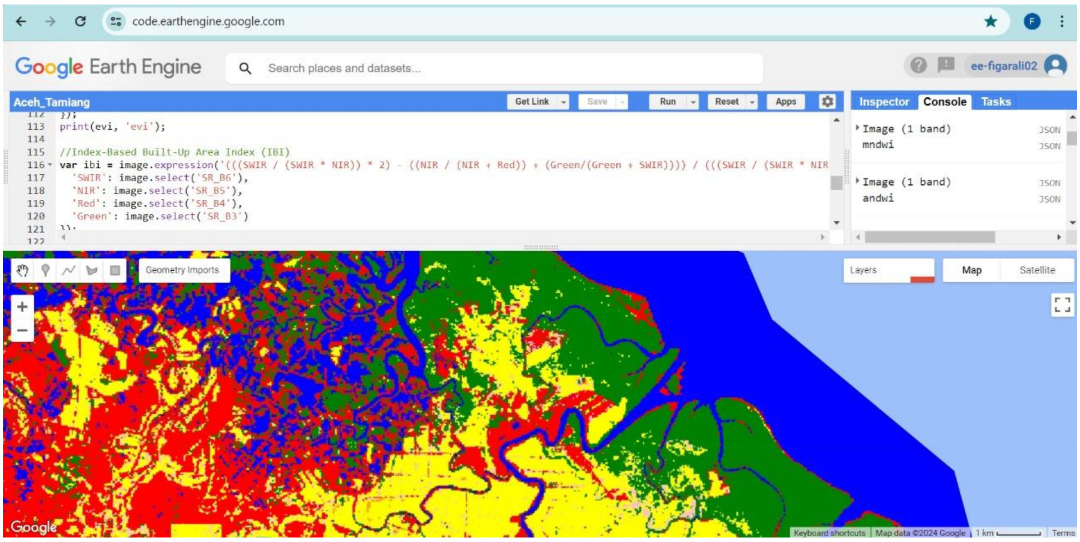

Figure 3. View of the GEE platform used in land cover change analysis, where the different colors shown indicate different land cover types.

The random forest algorithm in this study uses a combination of indices to identify the type of mangrove land cover in the study area. The index combination used is VWB-IC (Vegetation-Water-Built-up Index Combined), which has been proven to be able to display land cover types better than using a single index or band [62,63]. The selection of the index is based on consideration of the index function that adapts to the specific characteristics of the mangrove ecosystem. The vegetation index detects mangrove density [64]. In this research, the vegetation index was also applied to detect plantation land cover as one of the aspects that drives mangrove changes [65]. Meanwhile, the water index is involved because the effects of sea tides affect the physical condition of mangrove vegetation in the intertidal zone [63]. The built-up index studies mangrove land conversion due to urban expansion and development. The index used in detail is shown in Table 3.

Table 3. List of indices used, complete with formulas and references.

No	Method	Formula	Reference
1	Normalized Difference Vegetation Index (NDVI)	NDVI = (NIR - Red) / (NIR + Red)	Rouse *et al*. (1974)
2	Enhanced Vegetation Index (EVI)	EVI = ((NIR - Red) / ((NIR + 6) * (Red - 7.5) * (Blue + 1))) * 2.5	Huete et al. (2002)
3	Soil Adjusted Vegetation Index (SAVI)	SAVI = ((NIR - Red) / (NIR + Red +0.5)) * (1.0+0.5)	Rouse jr et al. (1974)
4	Specific Leaf Area Vegetation Index (SLAVI)	SLAVI = NIR / (Red + SWIR2)	Lymburner et al. (2000)
5	Atmospherically Resistant Vegetation Index (ARVI)	ARVI = (NIR - (Red - (1 * (Red - Blue)))) / (NIR + (Red - (1 * (Red - Blue))))	Kaufman et al. (1992)
6	Modified Normalized Difference Water Index (MNDWI)	MNDWI = Green - SWIR2 / Green + SWIR2	Xu (2006)
7	Augmented Normalized Difference Water Index (ANDWI)	ANDWI = (Blue + Green + Red - NIR - SWIR1 - SWIR2) / (Blue + Green + Red + NIR + SWIR1 + SWIR2)	Rad et al. (2021)
8	Green Normalized Difference Vegetation Index (GNDVI)	GNDVI = (NIR - Green) / (NIR + Green)	Gitelson et al. (1996)
9	Normalized Difference Built-up Index (NDBI)	NDBI = (SWIR - NIR) / (SWIR + NIR)	Zha et al. (2003)

Where :
Blue : Blue band, Green : green band, Red : red band, NIR: near-infrared band, SWIR : shortwave-infrared band

2.5. Accuration assesment

The results of the random forest classification algorithm sometimes need to match actual conditions. Therefore, it is essential to test the results of processing classification algorithms to determine the feasibility of the resulting data [66]. The accuracy assessment used in this research involves a confusion matrix table, which includes the overall accuracy (OA) and kappa statistics values as a test of the accuracy of the results of algorithm operations. The confusion matrix table summarizes the overall testing results of training data against validation data for each land cover class. Meanwhile, overall accuracy describes the quality of land cover classification results by calculating the proportion of samples predicted correctly by the algorithm with the total of all samples [67]. Kappa statistics is on of thestandard matrix test to assess the accuracy of classification [68]. The equation of overall accuracy and kappa statistics can be seen in formulas 1 and 2.

$$\text{Overall Accuracy (OA)} = \frac{1}{N}\sum_{i=1}^{r} X_{ii} \times 100\% \quad (1)$$

$$\text{Kappa} = \frac{\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r} X_{ii}\,(X_{i+} \times X_{+i})}{N^2\ \sum_{i=1}^{r} X_{ii}\,(X_{i+} \times X_{+i})} \quad (2)$$

3. Results and Discussion

3.1. Results

3.1.1. Mangrove identification

The results of mangrove detection using guided classification techniques showed that the mangrove ecosystem is distributed at river mouths and along the coastline, as shown in Figure 1. Based on Figure 1, Aceh Tamiang Regency has many river estuaries. Two rivers that flow into the coast of Aceh Tamiang Regency are the Mati River and the Tamiang River, which have a high diversity of fish species. In general, mangroves are distributed on the coast, both along coastlines and estuaries.

3.1.2. Dynamic change of mangrove

1. Mangrove status change over two decades

The results of the overlay analysis of mangrove land cover classification in Aceh Tamiang for the period 2000 to 2023 revealed three categories of status change: increase in area, decrease in area, and no change. The recapitulation of this change status is visualized in detail using a bar graph presented in Figure 4. The mangrove cover area was recorded at 13,270.85 hectares at the beginning of the period. However, the 2023 data shows a decrease to 11,871.63 hectares. The dynamics of this change are characterized by a reduction in mangrove area of 3,882.24 hectares, offset by adding new areas of 2,485.62 hectares.

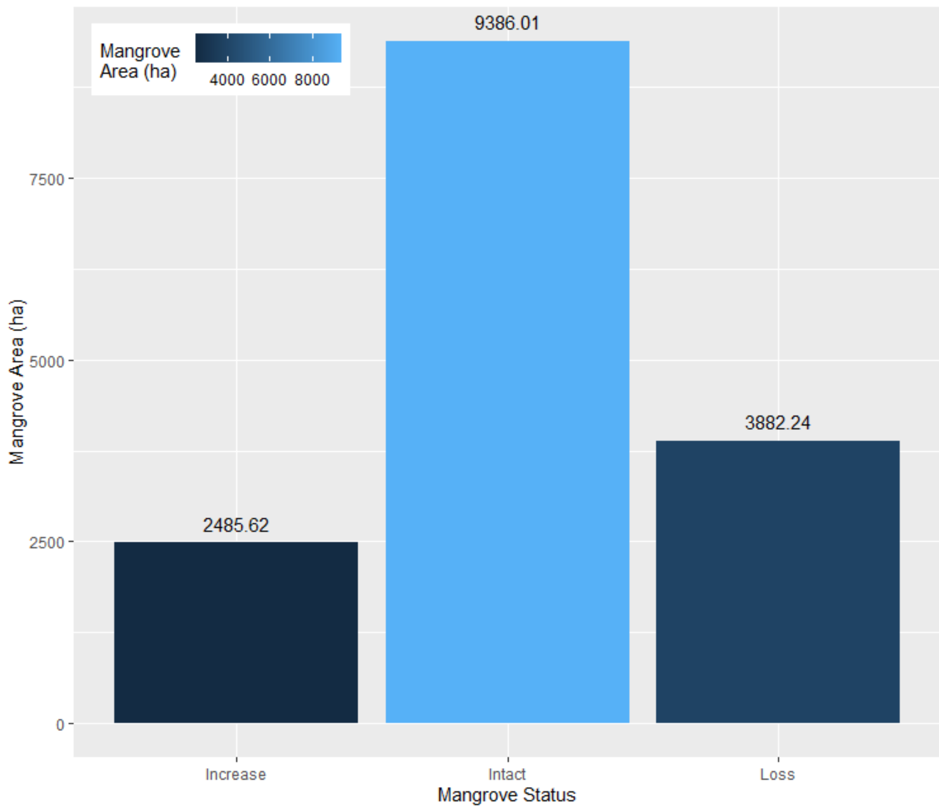

Figure 4. The bar graph showing the area of the mangrove ecosystem in three statuses is marked by an increase in area in line with the increase in color brightness.

2. Dynamics of land cover change from mangrove to other land cover types

The final change of mangroves in 2023 is presented as a dynamic map of mangrove use for 2000-2023, as shown in Figure 5. From 2000 to 2023, an area of 9386.01 ha of mangroves was intact (permanent) or unchanged. Other changes in mangrove areas in the same year period were into water bodies, ponds, plantation, and barren land with an area of 362.91 ha respectively, 768.57 ha, 2679.68 ha, and 71.07 ha. The changes in the status of mangrove land shown in Figure 4, the dynamics of which can be seen in Figure 5.

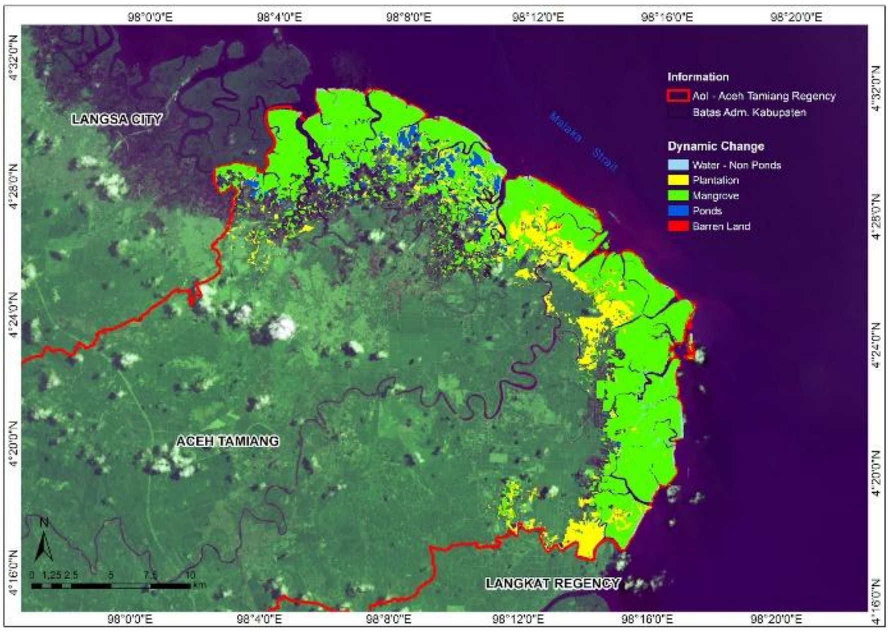

Figure 5. Distribution of the dynamics of mangrove land cover change to other land cover in Aceh Tamiang that occurred in the period 2000-2023.

3. Distribution of mangrove change status area

Over the course of two decades, mangroves that experienced land reduction were identified as changing into various types of land cover such as plantations, ponds, water bodies, and open land. The overall distribution of changes in mangrove status over two decades can be seen in Figure 6, which is dominated by the closer it is to the mainland, the more mangrove land is found to be damaged.

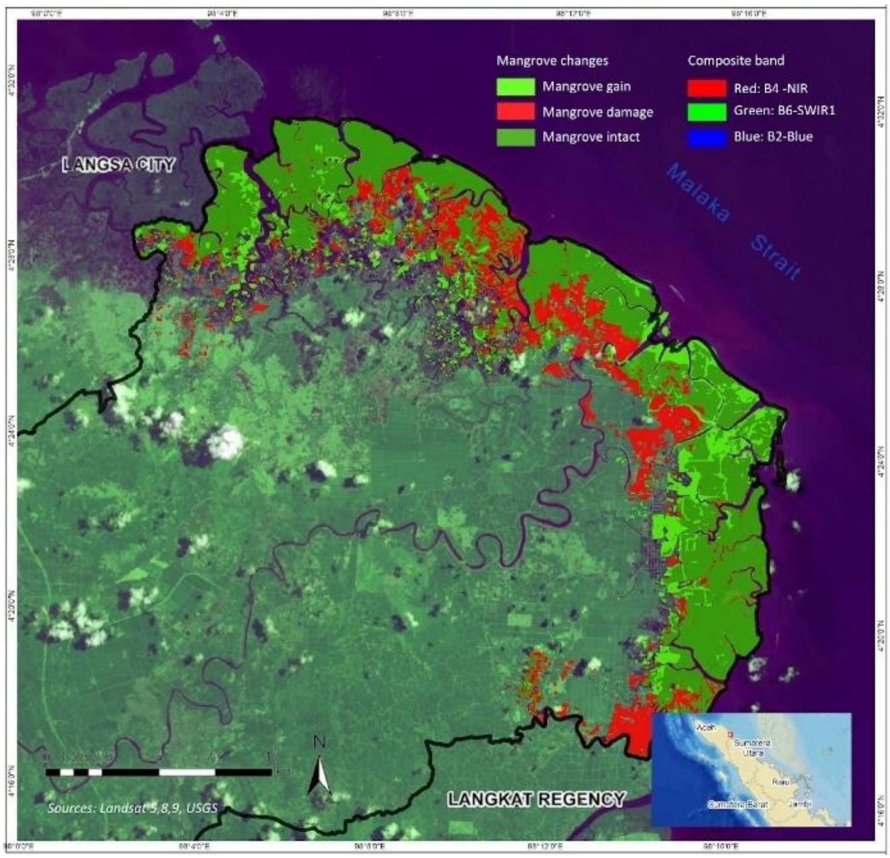

Figure 6. Distribution of changes in mangrove land status includes increase, reductions, and intact.

A comparison of mangrove land cover between the two decades can be seen in Figure 7. It is clear that the remaining mangrove land cover is located close to water bodies. In terms of area, how much has changed to other types of land cover is shown in Figure 8. The overall dynamics of the mangrove ecosystem in Aceh Tamiang over two decades (2000-2023) is a form of degradation phenomenon.

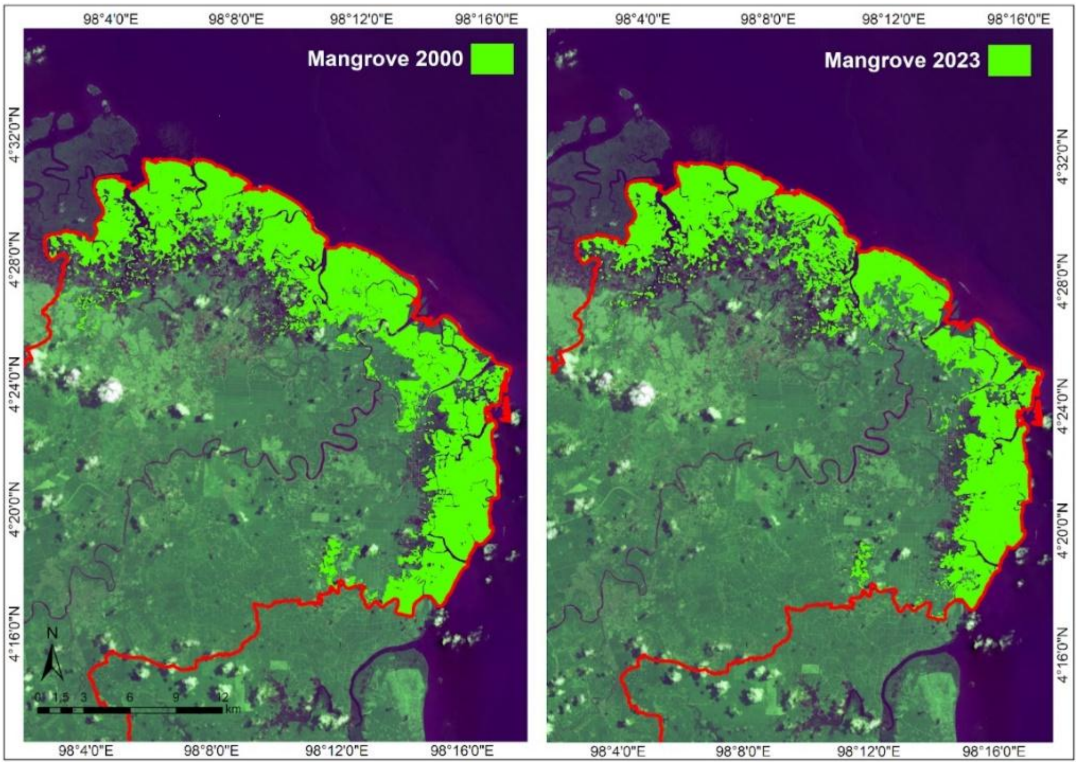

Figure 7. Distribution of mangroves in two different years two decades apart classified by machine learning classification method.

4. Area change transition over two decades

The transition of mangrove and non-mangrove land change over two decades is shown in the form of a Sankey diagram dominated by the change of mangrove land cover reduction to non-mangrove land cover class type plantation.

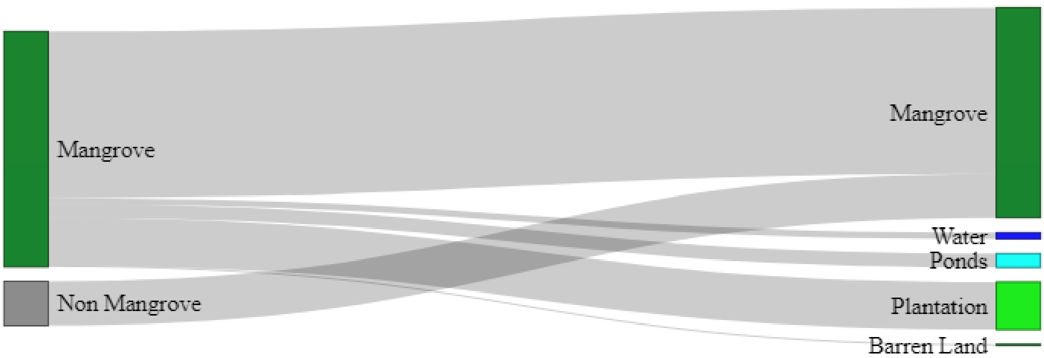

Figure 8. Sankey graphic shows the dynamics of mangrove change in Aceh Tamiang, characterized by land cover in 2000 on the left, and 2023 on the right.

3.1.3. Accuracy assessment

Accuracy assessment tested the performance of machine learning in carrying out something in the case of mangrove area detection or land classification. An accuracy assessment was done using the confusion matrix method in Tables 2000 and 2023. Based on the assessment results, the overall accuracy for detection in 2000 was 97.11%, with a kappa statistic of 95.98%. Meanwhile, the overall accuracy for 2023 was lower than in 2000, 79.10%, and the kappa statistic is 73.10%. However, user and producer accuracy in land classification 2023 was still relatively high, namely 94.61% and 100%.

Table 4. Confusion matrix and accuracy measures on 2000.

Land use land cover	Classification					Sum (User's)
	Water body	Mangrove	Agriculture	Bare land	Plantation	
Water body	1,717	0	0	0	0	1,717
Mangrove	0	1,633	3	0	0	1,636
Agriculture	0	74	388	5	29	496
Bare land	0	0	4	236	0	240
Plantation	0	19	10	0	734	763
Sum (Producer's)	1,717	1,726	398	241	763	

	User's accuracy (%)	Producer's accuracy (%)
Water body	100.00	100.00
Mangrove	94.61	100.00
Plantation	97.48	78.22
Agriculture	97.92	98.33
Bare land	96.19	96.19
Plantation		
Overall accuracy (OA)	97.11 %	
Kappa statistics	95.98 %	

Table 5. Confusion matrix and accuracy measures on 2023.

Land use land cover	Classification							Sum (user's)
	Water body	Mangrove	Plantation	Agriculture	Built up area	Agroforestry	Bare land	
Mangrove	371	0	0	0	0	0	0	371
Water body	0	36	12	0	1	0	0	49
Plantation	0	0	180	0	1	38	20	239
Agriculture	0	0	4	56	26	0	82	168
Built up area	0	0	0	0	27	0	12	39
Agroforestry	0	0	2	0	0	40	4	46
Bare land	0	0	0	0	0	3	66	69
Sum (produser)	371	36	196	56	50	81	184	

	User's accuracy (%)	Producer's accuracy (%)
Water body	73.46	100.00
Mangrove	100.00	100.00
Plantation	75.31	91.83
Agriculture	33.33	100.00
Built up area	69.23	54.00
Agroforestry	89.95	49.00
Bare land	95.65	35.00
Overall accuracy (OA)	79.10 %	
Kappa statistics	73.10 %	

3.2. Discussion

3.2.1. Mangrove identification

The coast of Aceh Tamiang district has several river estuaries that can carry sediment. The types of mangroves found on the coast of Aceh Tamiang are quite diverse, originating from the genera *Acrostichum* sp, *Acanthus* sp, *Avicennia* sp, *Bruguiera*, *Melastoma* sp., *Rhizophora* sp., *Sonneratia* sp., and *Xylocarpus* sp. [69]. According to Darmarini et al. [70] reported that there were ten types of mangroves found in the Lubuk Damar Coastal area, Aceh Tamiang, consisting of true and associated mangroves, namely *Avicennia alba*, *Bruguiera parviflora*, *Bruguiera sexangula*, *Sonneratia alba*, *Rhizophora apiculata*, *Acrostichum aureum*, *Aegiceras floridum*, *Excoecaria agallocha*, *Xylocarpus granatum*, and *Acanthus ilicifolius*. The community often uses the types of vegetation in the mangrove ecosystem for their produce, such as mangrove leaves (*Rhizophora* sp.), mangrove bark (*Rhizophora* sp.), pada fruit (*Sonneratia* sp.), api-api fruit (*Avicennia* sp.), noirish (*Xylocarpus granatum*), Nipah leaves (*Nypa fruticans*), and honey [71]. Mangroves found at river mouths have excellent conditions because they have a source of nutrients from river sediments. This is why most estuary river deltas have good-quality mangrove vegetation [72]. Factors that influence the biophysical characteristics of mangroves are climate and geographic factors. The climatic factor that most influences the condition of mangroves is rainfall because it causes puddles and affects salinity and organic material carried by rivers [73]. Geographical conditions influence the distribution of mangrove species found in an ecosystem [74].

The mangroves in this area are classified as severely damaged, exhibiting a tree density of merely 230 trees/ha. This degradation has led to significant ecological consequences, including a decline in the quality of potable water for local residents [75]. Darmarini et al. [76], and Arico et al. [77] also found from direct observations at the location that the mangroves in this area had experienced severe damage in the last 20 years due to human activities. The change in mangroves into water bodies can be caused by several factors, including climate change and the cutting down of mangroves around river areas; for example, the research of Asy'Ari et al. [78] revealed that there was damage to mangroves in the Subang Regency area due to logging. Climate change, which results in sea level rise, increased storms, changes in rainfall patterns, and increased temperatures, impacts mangrove forests, ranging from vegetation damage to loss of mangrove area [16]. Rising sea levels are the main factor in converting mangroves into water bodies because they increase flooding duration, which can lead to mangrove death [16,79]. Typhoons with increasing intensity impact mangrove forests because large waves can uproot mangrove trees, while strong winds can damage tree canopies (breaking branches and defoliating the canopy) [80–82]. The loss of mangroves at the outer limits causes changes in the coastline so that the land area decreases [83]. Changes in rainfall patterns will have an impact on the growth and distribution of mangroves; decreased rainfall with increased evaporation will result in increased salinity, decreased net primary productivity, changes in competition between mangrove species, decreased diversity of mangrove zones, decreased mangrove area [84–86]. Changes in precipitation patterns due to climate change can also cause increased pluvial sedimentation, which can increase freshwater input, resulting in loss of mangroves [16]. An increase in temperature can affect mangrove composition, productivity, phenology, and mangrove distribution because increasing temperature results in increased evaporation, which affects increasing salinity and aridity [16,80,87].

The dynamics of mangrove changes were also related to converting mangrove land into ponds. On a global scale, converting mangroves into ponds contributes the most significant percentage of world mangrove loss [17]. However, the results of this research found a different reality: the leading cause of mangrove loss was not aquaculture development but plantations. The same thing was also expressed by Arico et al. [77]. Even though pond construction is not the main factor causing mangrove loss in Aceh Tamiang, the conversion of mangroves into ponds in this study area is still relatively large because it reached 768.57 ha. Zulham et al. [88] reported an increase in the pond area in Aceh Tamiang in the 2017-2019 period with an expansion rate of 0.3% per year, where the expansion of the pond area has been proven to be carried out by the community towards mangroves in protected zones. The conversion of mangroves into ponds also occurs in several other mangrove areas close to the study location area, such as North Sumatra [89].

The dynamics of changing mangroves into plantations in Aceh Tamiang are generally converted into oil palm plantations. This can not only be revealed from direct observations resulting from satellite image data collection but also by Arico et al. [77]. Hasri et al. [75]found that in 2010, as many as 1940.95 ha (62.25%) of mangrove forests had been converted into oil palm plantations. However, changing mangroves into plantations can only sometimes be considered harmful for changes in mangrove forest areas. The positive and negative impacts of mangrove conversion due to plantations must be viewed from various other factors, such as increasing climate temperatures, marine typology, sea waves, and sediment supply [90]. Based on the results of this research analysis, it appears that plantations on the east coast have a positive impact. In contrast, plantations in other areas, such as Palembang, do not experience positive or negative changes (are stagnant) due to human activities such as mining, so the number of mangrove areas increases is the same as the number of areas. Mangroves are decreasing [91]. Plantation can have a positive impact because the results of the analysis found a change in non-mangrove areas into mangroves, as seen in Figure 8. The opening of plantations can result in the addition of appropriate sedimentation, thereby allowing propagules to spread more widely, ultimately increasing the area of mangroves [78,92].

This mangrove degradation causes a decline in the population of sea tuntong (*Batagor borneoensis*) as an endemic species of Aceh Tamiang because it eliminates the original habitat of this species [93]. The existence of fish, shrimp, and crabs is also threatened due to the destruction of the mangrove ecosystem as the habitat on which their lives depend. The community around the Aceh Tamiang mangroves plays a role in the dynamics of mangrove change. It is a disadvantaged party because the people of Aceh Tamiang are accustomed to cutting down mangrove trees to make firewood (charcoal) [76,77]. Meanwhile, as the disadvantaged party, the community experiences a decrease in economic income from fishing because the abundance of fish decreases due to the decrease in mangrove forest area.

This showed that under these conditions, the bias in detecting mangrove areas is still relatively low, so the performance of machine learning for detecting mangrove areas was relatively high. Detection of mangrove areas using various vegetation, water, and built-up indices has relatively high capabilities. The research resulted of Rahmawati and Asy'Ari [94] showed that using several indices in detecting mangrove areas with random forest algorithm has relatively high accuracy, reaching 96.50% and kappa statistics of 93%. Apart from that, this research also revealed that the SLAVI and RVI threshold values did not overlap, so it can be assumed that this index is quite sensitive to the presence of mangroves. Asy'Ari et al. [78] also reported that a combination of vegetation, water, and built-up indices could detect mangrove areas better than a combination of one type of index alone. Several indices have different abilities in detecting mangroves. Using the water index alone in detecting mangroves tends to overestimate while using the vegetation index tends to underestimate the size of the mangrove area [63].

The discovery revealed areas that have remained mangrove for two decades. This means these areas are classified as primary mangroves, which are more urgent to be preserved. Therefore, the findings of this study can be used as a basis for the study of mangrove land conservation zoning in Aceh Tamiang.

4. Conclusion

Spatiotemporal analysis using random forest classification and ArcMap revealed a decrease in mangrove area in Aceh Tamiang from 13,270.85 ha in 2000 to 9,386.01 ha in 2023. The changes in other mangrove areas in the same period were to water bodies, ponds, plantation, and barren land with an area of 362.91 ha; 768.57 ha; 2679.68 ha; and 71.07 ha, respectively. The dynamics of mangrove change in the form of mangrove area reduction include the conversion of mangrove forests into water bodies (non-ponds), plantations, ponds, and open land. Mangrove conversion into water bodies is driven by two factors: anthropogenic activities and climate change. Anthropogenic activities such as logging can reduce the area of mangroves close to the river. Climate change affects changes in the area of the outer mangroves due to the regression of the coastline. Climate change also affects the physiology of mangrove tree vegetation, resulting in a decrease in the ability/resilience of the forest. The conversion of mangroves to ponds in the study area was not a major factor in the decline of the mangrove area (in contrast to the global scale). The conversion of mangroves to oil palm plantations in the case of the study area is classified as having a positive impact in the form of additional sedimentation, making it easier for propagules to spread more widely.

Eventually, the dynamics of mangrove change that occurred over two decades resulted in more mangrove area lost than mangrove area gained. This led to the mangrove forest's degradation, affecting the original habitat's biodiversity and the surrounding coastal communities.

Author Contributions

KPM: Conceptualization, Methodology, Investigation, Software, Writing - Review & Editing; **RA**: Conceptualization, Methodology, Investigation, Software, Writing - Review & Editing; **ADR**: Conceptualization, Writing - Review & Editing, **AD:** Conceptualization, Methodology, Investigation, Software - Writing; **AU:** Conceptualization, Investigation, Writing; **RFP:** Conceptualization – Writing; **NPZ:** Conceptualization – Writing; **RP:** Conceptualization – Writing; **YS:** Conceptualization – Writing.

Conflicts of interest

There are no conflicts to declare

Acknowledgements

The authors thank the IPB SSRS Association for facilitating this research.

References

1. Clough, B. Continuing the Journey Amongst Mangroves; ISME: Okinawa, 2013;
2. Lu, C.; Liu, J.; Jia, M.; Liu, M.; Man, W.; Fu, W.; Zhong, L.; Lin, X.; Su, Y.; Gao, Y. Dynamic Analysis of Mangrove Forests Based on an Optimal Segmentation Scale Model and Multi-Seasonal Images in Quanzhou Bay, China. Remote Sens (Basel) **2018**, 10, doi:10.3390/RS10122020.
3. Rahman; Lokollo, F.F.; Manuputty, G.D.; Hukubun, R.D.; Krisye; Maryono; Wawo, M.; Wardiatno, Y. A Review on the Biodiversity and Conservation of Mangrove Ecosystems in Indonesia. Biodivers Conserv **2024**, 33, 875–903, doi:10.1007/s10531-023-02767-9.
4. Spalding, M.; McIvor, A.; Tonneijck, F.H.; Tol, S.; van Eijk, P. Mangroves for Coastal Defence. Guidelines for Coastal Managers \& Policy Makers; 2014;
5. Asari, N.; Suratman, M.N.; Mohd Ayob, N.A.; Abdul Hamid, N.H. Mangrove as a Natural Barrier to Environmental Risks and Coastal Protection. In Mangroves: Ecology, Biodiversity and Management; Springer Singapore: Singapore, 2021; pp. 305–322.
6. Hendy, I.W.; Michie, L.A.; Taylor, B.W. Habitat Creation and Biodiversity Maintenance in Mangrove Forests: Teredinid Bivalves as Ecosystem Engineers. PeerJ **2014**, 2, doi:10.7717/PEERJ.591.
7. Nunoo, F.K.E.; Agyekumhene, A. Mangrove Degradation and Management Practices along the Coast of Ghana. Agricultural Sciences **2022**, 13, 1057–1079, doi:10.4236/as.2022.1310065.
8. Meng, Y.; Bai, J.; Gou, R.; Cui, X.; Feng, J.; Dai, Z.; Diao, X.; Zhu, X.; Lin, G. Relationships Between Above- and Below-Ground Carbon Stocks in Mangrove Forests Facilitate Better Estimation of Total Mangrove Blue Carbon. Carbon Balance Manag **2021**, 16, doi:10.1186/S13021-021-00172-9.
9. Dinilhuda, A.; Akbar, A.A.; Jumiati; Herawaty, H. Potentials of Mangrove Ecosystem as Storage of Carbon for Global Warming Mitigation. Biodiversitas **2020**, 21, doi:10.13057/biodiv/d211141.
10. Kusmana, C.; Sukristijiono, S. Mangrove Resource Uses by Local Community in Indonesia. Journal of Natural Resources and Environmental Management **2016**, 6, 217–224.
11. Debrot, A.O.; Veldhuizen, A.; van den Burg, S.W.K.; Klapwijk, C.J.; Islam, Md.N.; Alam, Md.I.; Ahsan, Md.N.; Ahmed, M.U.; Hasan, S.R.; Fadilah, R.; et al. Non-Timber Forest Product Livelihood-Focused Interventions in Support of Mangrove Restoration: A Call to Action. Forests **2020**, 11, 1224, doi:10.3390/f11111224.
12. Palacios, M.L.; Cantera, J.R. Mangrove Timber Use as an Ecosystem Service in the Colombian Pacific. Hydrobiologia **2017**, 803, 345–358, doi:10.1007/s10750-017-3309-x.

13. Adriyanti, D.T.; Putri, T.W.S.; Mindaryani, A.; Prasetya, A.; Petrus, H.T.B.M. Community Empowerment through Sustainable Utilisation of Mangrove Forests for the Production of Natural Dyes with An Environmentally Friendly System (Phase I: Increasing Awareness and Knowledge Enhancement). Jurnal Pengabdian kepada Masyarakat (Indonesian Journal of Community Engagement) **2023**, 9, 38, doi:10.22146/jpkm.70455.

14. Habiba, A.M.S.; Yemul, N.B.; Ghalme, R.L. Use of Mangrove Leaves (Rhizophora Mucronath) Extract as a Biofertilizer for Seed Germination. FLORA AND FAUNA **2020**, 26, doi:10.33451/florafauna.v26i1pp49-57.

15. Tahang, H.; Amiluddin, A.; Amir, F.; Firman, F. Economic Valuation of Mangrove Forest Ecosystem in Sinjai. Torani Journal of Fisheries and Marine Science **2018**, 71–80, doi:10.35911/torani.v1i2.4444.

16. Ward, R.D.; Friess, D.A.; Day, R.H.; Mackenzie, R.A. Impacts of Climate Change on Mangrove Ecosystems: A Region by Region Overview. Ecosystem Health and Sustainability **2016**, 2, doi:10.1002/ehs2.1211.

17. FAO The World's Mangroves 2000–2020; FAO: Rome, 2023;

18. Contessa, V.; Dyson, K.; Vivar Mulas, P.P.; Kindgard, A.; Liu, T.; Saah, D.; Tenneson, K.; Pekkarinen, A. Uncovering Dynamics of Global Mangrove Gains and Losses. Remote Sens (Basel) **2023**, 15, 3872, doi:10.3390/rs15153872.

19. Bunting, P.; Rosenqvist, A.; Hilarides, L.; Lucas, R.M.; Thomas, N.; Tadono, T.; Worthington, T.A.; Spalding, M.; Murray, N.J.; Rebelo, L.-M. Global Mangrove Extent Change 1996–2020: Global Mangrove Watch Version 3.0. Remote Sens (Basel) **2022**, 14, 3657, doi:10.3390/rs14153657.

20. KLHK The State of Indonesia's Forests 2022 Towards FOLU Net Sink 2030.; KLHK: Jakarta, 2022;

21. Sasmito, S.D.; Basyuni, M.; Kridalaksana, A.; Saragi-Sasmito, M.F.; Lovelock, C.E.; Murdiyarso, D. Challenges and Opportunities for Achieving Sustainable Development Goals through Restoration of Indonesia's Mangroves. Nat Ecol Evol **2023**, 7, 62–70, doi:10.1038/s41559-022-01926-5.

22. Rahman; Ceanturi, A.; Tuahatu, J.W.; Lokollo, F.F.; Supusepa, J.; Hulopi, M.; Permatahati, Y.I.; Lewerissa, Y.A.; Wardiatno, Y. Mangrove Ecosystems in Southeast Asia Region: Mangrove Extent, Blue Carbon Potential and CO2 Emissions in 1996–2020. Science of The Total Environment **2024**, 915, 170052, doi:10.1016/j.scitotenv.2024.170052.

23. Arifanti, V.B.; Sidik, F.; Mulyanto, B.; Susilowati, A.; Wahyuni, T.; Subarno, S.; Yulianti, Y.; Yuniarti, N.; Aminah, A.; Suita, E.; et al. Challenges and Strategies for Sustainable Mangrove Management in Indonesia: A Review. Forests **2022**, 13, 695, doi:10.3390/f13050695.

24. Sunkur, R.; Kantamaneni, K.; Bokhoree, C.; Rathnayake, U.; Fernando, M. Mangrove Mapping and Monitoring Using Remote Sensing Techniques towards Climate Change Resilience. Sci Rep **2014**, 14, 1–14.

25. Pham, T.D.; Yokoya, N.; Bui, D.T.; Yoshino, K.; Friess, D.A. Remote Sensing Approaches for Monitoring Mangrove Species, Structure, and Biomass: Opportunities and Challenges. Remote Sens (Basel) **2019**, 11, doi:10.3390/RS11030230.

26. Elmahdy, S.I.; Ali, T.; Mohamed, M.M.; Howari, F.M.; Abouleish, M.; Simonet, D. Spatiotemporal Mapping and Monitoring of Mangrove Forests Changes from 1990 to 2019 in the Northern Emirates, UAE Using Random Forest, Kernel Logistic Regression and Naive Bayes Tree Models. Front Environ Sci **2020**, 8, 102, doi:10.3389/FENVS.2020.00102.

27. Junianto, M.; Sugianto, S.; Basri, H. Analysis of Changes in Mangrove Land Cover in West Langsa District, Langsa. Jurnal Penelitian Pendidikan IPA **2023**, 9, 1155–1162, doi:10.29303/jppipa.v9i3.2963.

28. Irawan, S.; Kurniawan, D.E.; Anurogo, W.; Lubis, M.Z. Mangrove Distribution in Riau Islands Using Remote Sensing Technology. Journal of Applied Geospatial Information **2017**, 1, 58–62, doi:10.30871/jagi.v1i2.456.

29. Aritonang, L.; Septyani, E.; Maria, L. Pemetaan Perubahan Luasan Mangrove Melalui Analisis Citra Satelit Landsat Di Tangkolak Barat, Karawang, Jawa Barat. Jurnal Geosains dan Remote Sensing **2022**, 3, 30–35, doi:10.23960/jgrs.2022.v3i1.69.

30. Febrianto, S.; Syafina, H.A.; Latifah, N.; Muskananfola, M.R. Dinamika Perubahan Luasan Dan Kerapatan Ekosistem Mangrove Di Kawasan Taman Nasional Sembilang Menggunakan Citra Satelit Landsat 8. Jurnal Kelautan Tropis **2022**, 25, 369–377, doi:10.14710/jkt.v25i3.14909.

31. Febriandi, F. The Estimation of Mangroves Area and Density of Mangroves Changes Use the Remote Sensing Data at Northheast Province of Aceh, Indonesia. Sumatra Journal of Disaster, Geography and Geography Education **2017**, 1, 105, doi:10.24036/sjdgge.v1i1.43.

32. Haikal, B.F.; Susilo, S.B.; Agus, S.B.; Oktavian, R.Z. Mapping Mangrove Distribution Using Remote Sensing Technology in Harapan, Kelapa and Pamegaran Seribu Islands National Park. IOP Conf Ser Earth Environ Sci **2021**, 944, 012046, doi:10.1088/1755-1315/944/1/012046.
33. Raynaldo, A.; Mukhtar, E.; Novarino, W. Mapping and Change Analysis of Mangrove Forest by Using Landsat Imagery in Mandeh Bay, West Sumatra, Indonesia. Aquaculture, Aquarium, Conservation & Legislation **2020**, 13, 2144–2151.
34. Ramandalush, F.; Santoso, A.I.; A, S.E.; Hutahean, A.A. Analisis Data Penginderaan Jauh Untuk Mendeteksi Perubahan Luasan Mangrove Sebagai Sarana Pelindung Ekosistem Pantai (Studi Kasus Di Kema, Kabupaten Minahasa Utara, Sulawesi Utara). Jurnal Chart Datum **2022**, 2, 88–97, doi:10.37875/chartdatum.v2i1.78.
35. Fletcher, C.; Ripple, W.J.; Newsome, T.; Barnard, P.; Beamer, K.; Behl, A.; Bowen, J.; Cooney, M.; Crist, E.; Field, C.; et al. Earth at Risk: An Urgent Call to End the Age of Destruction and Forge a Just and Sustainable Future. PNAS Nexus **2024**, 3, doi:10.1093/pnasnexus/pgae106.
36. NATSIR, M.; ULYA, Z.; FITRIANI, R. Mangrove Forest Utilization Policies Reconceptualized with a View to Improving the Regional Economy in Aceh Tamiang District, Indonesia. Biodiversitas **2023**, 23, doi:10.13057/biodiv/d231256.
37. Charles, A.C.; Armstrong, A.; Nnamdi, O.C.; Innocent, M.T.; Obiageri, N.J.; Begianpuye, A.F.; Timothy, E.E. Review of Spatial Analysis as a Geographic Information Management Tool. American Journal of Engineering and Technology Management **2024**, 9, 8–20.
38. Balabied, S.A.A.; Eid, H.F. Utilizing Random Forest Algorithm for Early Detection of Academic Underperformance in Open Learning Environments. PeerJ Comput Sci **2023**, 9, e1708.
39. Gibbons, C.; Richards, S.; Valderas, J.M.; Campbell, J. Supervised Machine Learning Algorithms Can Classify Open-Text Feedback of Doctor Performance With Human-Level Accuracy. J Med Internet Res **2017**, 19, e65.
40. Mukherjee, S.; Tamayo, P.; Rogers, S.; Rifkin, R.; Engle, A.; Campbell, C.; Golub, T.R.; Mesirov, J.P. Estimating Dataset Size Requirements for Classifying DNA Microarray Data. **2003**, 10, doi:10.1089/106652703321825928.
41. Davoudi Moghaddam, D.; Rahmati, O.; Panahi, M.; Tiefenbacher, J.P.; Darabi, H.; Haghizadeh, A.; Haghighi, A.T.; Nalivan, O.A.; Bui, D.T. The Effect of Sample Size on Different Machine Learning Models for Groundwater Potential Mapping in Mountain Bedrock Aquifers. **2020**, 187, doi:10.1016/J.CATENA.2019.104421.
42. Adadi, A. A Survey on Data-efficient Algorithms in Big Data Era. J Big Data **2021**, 8, 24, doi:10.1186/s40537-021-00419-9.
43. Moghaddam, D.D.; Rahmati, O.; Panahi, M.; Tiefenbacher, J.; Darabi, H.; Haghizadeh, A.; Haghighi, A.T.; Nalivan, O.A.; Tien Bui, D. The Effect of Sample Size on Different Machine Learning Models for Groundwater Potential Mapping in Mountain Bedrock Aquifers. Catena (Amst) **2020**, 187, 104421, doi:10.1016/j.catena.2019.104421.
44. Moraes, D.; Benevides, P.; Costa, H.; Moreira, F.D.; Caetano, M. Influence of Sample Size in Land Cover Classification Accuracy Using Random Forest and Sentinel-2 Data in Portugal. In Proceedings of the 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS; IEEE, July 11 2021; pp. 4232–4235.
45. Alam, M.Z.; Rahman, M.S.; Rahman, M.S. A Random Forest Based Predictor for Medical Data Classification Using Feature Ranking. **2019**, 15, doi:10.1016/J.IMU.2019.100180.
46. Short, N.M.; Lowan Jr, P.D.; Freden, S.C.; Finch Jr, W.A. Mission to Earth: Landsat Views the World; NASA Special Publication 360, NASA Science and Technical Information Office, Washington, D.C., 1976;
47. Chander, G.; Markham, B.L.; Barsi, J.A. Revised Landsat-5 Thematic Mapper Radiometric Calibration. IEEE Geoscience and Remote Sensing Letters **2007**, 4, 490–494, doi:10.1109/LGRS.2007.898285.
48. Acharya, T.; Yang, I. Exploring Landsat 8. . International Journal of IT, Engineering and Applied Sciences Research (IJIEASR) **2015**, 4, 4–10.
49. United States Geological Survey Landsat 8: U.S. Geological Survey Fact Sheet 2013--3060 2013.
50. Reuter, D.C.; Richardson, C.; Pellerano, F.A.; Irons, J.R.; Allen, R.G.; Anderson, M.C.; Jhabvala, M.D.; Lunsford, A.W.; Montanaro, M.; Smith, R. The Thermal Infrared Sensor ({TIRS}) on {Landsat} 8: {Design} {Overview} and {Pre}-Launch {Characterization}. Remote Sens (Basel) **2015**, 7, doi:10.3390/RS70101135.
51. Xu, H.; Ren, M.; Lin, M. Cross-Comparison of {Landsat}-8 and {Landsat}-9 Data: A Three-Level Approach Based on Underfly Images. Remote Sens (Basel) **2024**, 61, doi:10.1080/15481603.2024.2318071.
52. Khyami, A. Impact of Land Cover Change on Land Surface Temperature over Greater Beirut Area – Lebanon. Journal of Geoinformatics & Environmental Research **2021**, 2, 14–27, doi:10.38094/jgier2121.

53. Gorelick, N.; Hancher, M.; Dixon, M.J.; Ilyushchenko, S.; Thau, D.; Moore, R. {Google Earth Engine}: {Planetary}-Scale {Geospatial} {Analysis} for {Everyone}. Remote Sens Environ **2017**, 202, doi:10.1016/J.RSE.2017.06.031.
54. Kumar, L.; Mutanga, O. Google Earth Engine Applications Since Inception: Usage, Trends, and Potential. Remote Sens (Basel) **2018**, 10, doi:10.3390/RS10101509.
55. Parente, L.; Taquary, E.; Silva, A.; Souza, C.; Ferreira, L. Next Generation Mapping: Combining Deep Learning, Cloud Computing, and Big Remote Sensing Data. Remote Sens (Basel) **2019**, 11, 2881, doi:10.3390/rs11232881.
56. Padarian, J.; Minasny, B.; McBratney, A.B. Using Google's Cloud-Based Platform for Digital Soil Mapping. Comput Geosci **2015**, 83, doi:10.1016/J.CAGEO.2015.06.023.
57. Velastegui-Montoya, A.; Montalván-Burbano, N.; Carrión-Mero, P.; Rivera-Torres, H.; Sadeck, L.; Adami, M. Google Earth Engine: A Global Analysis and Future Trends. Remote Sens (Basel) **2023**, 15, 3675, doi:10.3390/rs15143675.
58. Belgiu, M.; Drăguţ, L. Random Forest in Remote Sensing: A Review of Applications and Future Directions. ISPRS Journal of Photogrammetry and Remote Sensing **2016**, 114, doi:10.1016/J.ISPRSJPRS.2016.01.011.
59. Breiman, L. Random Forests. Mach Learn **2001**, 45, 5–32, doi:10.1023/A:1010933404324.
60. Wang, P.; Zhang, X.; Shi, L.; Liu, M.; Liu, G.; Cao, C.; Wang, R. Assessment of Sea-Ice Classification Capabilities during Melting Period Using Airborne Multi-Frequency PolSAR Data. Remote Sens (Basel) **2024**, 16, doi:10.3390/rs16061100.
61. Belgiu, M.; Drăguţ, L. Random Forest in Remote Sensing: A Review of Applications and Future Directions. ISPRS Journal of Photogrammetry and Remote Sensing **2016**, 114, 24–31, doi:10.1016/j.isprsjprs.2016.01.011.
62. Tran, T. V; Reef, R.; Zhu, X. A Review of Spectral Indices for Mangrove Remote Sensing. Remote Sens (Basel) **2022**, 14, doi:10.3390/rs14194868.
63. Rahmawati, A.; Asy'Ari, R.; Fathonah, M.; Zamani, N.; Pramulya, R.; Setiawan, Y. Vegetation-Water-Built up Index Combined: Algorithm Indices Combination for Characterization and Distribution of Mangrove Forest Through Google Earth Engine. CELEBES Agricultural. **2022**, 3, 20–42.
64. Aulia, Z.S.; Pribadi, R.; Helmi, M. The Use of Vegetation Indices on Temporal Mangrove Condition: A Case Study on Timbulsloko and Bedono, Demak. Jurnal Ilmiah Perikanan dan Kelautan **2023**, 16, 220–233, doi:10.20473/jipk.v16i1.43935.
65. Moriya, É.A.S.; Imai, N.N.; Tommaselli, A.M.G.; Honkavaara, E.; Rosalen, D.L. Design of Vegetation Index for Identifying the Mosaic Virus in Sugarcane Plantation: A Brazilian Case Study. Agronomy **2023**, 13, 1542, doi:10.3390/agronomy13061542.
66. Yang, Y.; Yang, D.; Wang, X.; Zhang, Z.; Nawaz, Z. Testing Accuracy of Land Cover Classification Algorithms in the Qilian Mountains Based on GEE Cloud Platform. Remote Sens (Basel) **2021**, 13, 5064.
67. Li, Y.; Zhu, X.; Pan, Y.; Gu, J.; Zhao, A.; Liu, X. A Comparison of Model-Assisted Estimators to Infer Land Cover/Use Class Area Using Satellite Imagery. Remote Sens (Basel) **2014**, 6, doi:10.3390/RS6098904.
68. Dash, P.; Sanders, S.L.; Parajuli, P.; Ouyang, Y. Improving the Accuracy of Land Use and Land Cover Classification of Landsat Data in an Agricultural Watershed. Remote Sens (Basel) **2023**, 15, 4020, doi:10.3390/rs15164020.
69. Mawardi, M.; Elisa, E. Keanekaragaman Mangrove Di Pantai Kupang Desa Lubuk Damar Kecamatan Seruway Kabupaten Aceh Tamiang. Jurnal Jeumpa **2017**, 4, 61–67.
70. Darmarini, A.S.; Wardiatno, Y.; Partono, T.; Soewardi, K.; Samosir, A.M.; Zainuri, M. Structure of Mangrove Ecosystem in Lubuk Damar Coast, Seruway, Aceh Tamiang. Jurnal Pengelolaan Sumberdaya Alam dan Lingkungan (Journal of Natural Resources and Environmental Management) **2022**, 12, 72–81, doi:10.29244/jpsl.12.1.72-81.
71. Kasnadiya, K.; Subhan, S.; Erida, G. Identifikasi Dan Pemanfaatan Hasil Hutan Bukan Kayu Pada Ekosistem Mangrove Dalam Kawasan Kesatuan Pengelolaan Hutan Wilayah III Aceh (Studi Kasus: Kabupaten Aceh Tamiang). Jurnal Ilmiah Mahasiswa Pertanian **2023**, 8, 590–596.
72. Giri, C.; Long, J.; Abbas, S.; Murali, M.; Qamer, F.M.; Pengra, B.W.; Thau, D. Distribution and Dynamics of Mangrove Forests of South Asia. J Environ Manage **2015**, 148, doi:10.1016/J.JENVMAN.2014.01.020.
73. Osland, M.J.; Feher, L.C.; López-Portillo, J.; Day, R.H.; Suman, D.O.; Guzmán Menéndez, J.M.; Rivera-Monroy, V.H. Mangrove Forests in a Rapidly Changing World: Global Change Impacts and Conservation Opportunities Along the Gulf of Mexico Coast. Estuar Coast Shelf Sci **2018**, 214, doi:10.1016/J.ECSS.2018.09.006.

74. Raw, J.; Godbold, J.A.; Van Niekerk, L.; Adams, J.B. Drivers of Mangrove Distribution at the High-Energy, Wave-Dominated, Southern African Range Limit. Estuar Coast Shelf Sci **2019**, 226, doi:10.1016/J.ECSS.2019.106296.

75. Hasri, K.; Basri, H.; Indra, I. Dampak Alih Fungsi Lahan Terhadap Nilai Ekosistem Mangrove Di Kecamatan Seruway Kabupaten Aceh Tamiang. . Jurnal Manajemen Sumberdaya Lahan **2014**, 30, 396–405.

76. Darmarini, A.S.; Wardiatno, Y.; Prartono, T.; Soewardi, K.; Samosir, A.M.; Zainuri, M. Mangrove Community Structure in Lubuk Damar Coast, Seruway, Aceh Tamiang. Journal of Natural Resources and Environmental Management **2021**, 12, 72–81.

77. Arico, Z.; Rahman, A.; Akob, B.; Jayanthi, S. Sustainable Development Based on Indigenous Knowledge in the Coastal Area of Aceh Tamiang, Aceh, Indonesia. Kasetsart Journal of Social Sciences **2023**, 44, 739–750.

78. Asy'Ari, R.; Rahmawati, A.D.; Dzulfigar, A.; Marfi, K.P.; Ulfa, A.; Puspitasari, R.F.; Raihan, F.; Aslam, M.F.; Saputri, H.R.; Madinu, A.M.A.; et al. Mangrove Damage vs Succession: An Opinion on the Journey of Mangrove Investigation Studies in Subang Regency Coast Area. SSRS Journal A: Agro-Environmental Research **2023**, 1, 1–6.

79. He, M.; Wang, X.; Zou, C.; Dai, B.; Jin, L. A Commodity Classification Framework Based on Machine Learning for Analysis of Trade Declaration. Symmetry (Basel) **2021**, 13, doi:10.3390/SYM13060964.

80. Smith, T.J.; Robblee, M.B.; Wanless, H.R.; Doyle, T.W. Mangroves, Hurricanes and Lightning Strikes. Estuaries **1994**, 44, doi:10.2307/1312230.

81. Doyle, T.W.; Smith, T.J.; Robblee, M.B. Wind Damage Effects of Hurricane Andrew on Mangrove Communities Along the Southwest Coast of Florida, USA. **1995**.

82. Xiong, L.; Lagomasino, D.; Charles, S.P.; Castañeda-Moya, E.; Cook, B.D.; Redwine, J.; Fatoyinbo, L. Quantifying Mangrove Canopy Regrowth and Recovery After Hurricane Irma with Large-Scale Repeat Airborne Lidar in the Florida Everglades. Journal of Applied Geography **2022**, 114, doi:10.1016/j.jag.2022.103031.

83. Madinu, A.M.A.; Jouhary, N.A.; Ulfa, A.; Rahmadhanti, I.N.; Pudjawati, N.H.; Asy'Ari, R.; Zamani, N.P.; Pramulya, R.; Setiawan, Y. Monitoring of Coastal Dynamics at Subang Regency Using Landsat Collection Data and Cloud Computing Based. BIO Web Conf **2024**, 106, 4005, doi:10.1051/bioconf/202410604005.

84. Field, C. Impacts of Expected Climate Change on Mangroves. Hydrobiologia **1995**, 295, 75–81.

85. Ellison, J.C. Vulnerability Assessment of Mangroves to Climate Change and Sea-Level Rise Impacts. Aquat Bot **2015**, 23, doi:10.1007/S11273-014-9397-8.

86. Gilman, E.; Ellison, J.C.; Duke, N.C.; Field, C.D. Threats to Mangroves from Climate Change and Adaptation Options: A Review. Aquat Bot **2008**, 89, doi:10.1016/J.AQUABOT.2007.12.009.

87. Ball, M.C.; Sobrado, M.A. Ecophysiology of Mangroves: Challenges in Linking Physiological Processes with Patterns in Forest Structure. In Advances in Plant Physiological Ecology; Press, M.C., Scholes, J.D., Barker, M.G., Eds.; Blackwell Science: Oxford, UK, 2002; pp. 331–346.

88. Zulham, A.; Shafitri, N.; Wardono, B.; Pramoda, R.; Yuliati, C.; Purnomo, A.H. Collective Actions to Support Sustainable Aquaculture: Evidence from Brackish Water Ponds Area in Aceh Tamiang. BIO Web Conf **2023**, 74, 1008.

89. Fanbudy, A.R.; Solfiyeni; Mukhtar, E. Mangrove Distribution in North Sumatera, Indonesia: A Review. IJPSAT **2024**, 42, 158–170.

90. Ellison, J.C. Factors Influencing Mangrove Ecosystems; Springer Singapore, 2021;

91. Eddy, S.; Setiawan, A.A.; Taufik, M.; Oktavia, M.; Utomo, B.; Milantara, N. Loss of Carbon Stock as an Impact of Anthropogenic Activities in a Protected Mangrove Forest. **2023**, 24, doi:10.13057/biodiv/d241211.

92. Yang, J.; Gao, J.; Cheung, A.; Liu, B.; Schwendenmann, L.; Costello, M.J. Vegetation and Sediment Characteristics in an Expanding Mangrove Forest in New Zealand. Estuar Coast Shelf Sci **2013**, 134, 11–18, doi:10.1016/j.ecss.2013.09.017.

93. Andiny, P.; Wahyuningsih, P.; Meutia, R.; Junita, A. Perancangan Destinasi Branding Desa Wisata Pusong Kapal Kecamatan Seruway Kabupaten Aceh Tamiang. Buletin Al-Ribaath **2022**, 19, 77–81.

94. Rahmawati, A.; Asy'Ari, R. Google Earth Engine: Pemanfaatan Platform Pemetaan Berbasis Cloud Computing Dalam Mendeteksi Distribusi Mangrove Dengan Citra Sentinel-2 Di Jakarta. In Proceedings of the Seminar Nasional Geomatika 2021: Inovasi Geospasial dalam Pengurangan Risiko Bencana; Rahadiati, A., Ed.; Badan Informasi Geospasial: Online, 2021.