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# ANALYSIS CHANGES IN MANGROVE FOREST COVER USING MULTI-SENSOR IMAGE IN NORTH LUWU DISTRICT SOUTH SULAWESI 2015-2020

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**Abstract**

Mangrove forest is one of the essential components of natural ecosystems. Mangrove forests have various essential functions, such as holding land sediments, tsunamis, and ocean waves, storing large amounts of carbon, and providing various other benefits for coastal and land areas. However, the conversion of mangrove forests has reduced and degraded mangrove land. Therefore, monitoring and conserving land changes in mangrove forests must be carried out to determine the effects on land ecosystems and coastal areas. Remote sensing has the spatial ability to analyze changes in mangrove ecosystems in coastal regions temporally because it has the advantage of using satellite imagery data. This study compares the classification method using multiple image sensors to analyze land cover changes in mangrove forests in North Luwu Regency, South Sulawesi, in 2015-2020. The technique used in this research is the classification of Object-Based Image Analysis (OBIA) and the variety of Maximum Likelihood. The results of Sentinel-1 image analysis using Maximum Likelihood provide information on changes in mangrove land cover during 2015-2020 with an area of 449.17 (Ha), while the results of Landsat 8 analysis using (OBIA) provide information on changes in mangrove land cover 596 (Ha).

**Keywords:** Optics, Radar, OBIA, Maximum Likelihood, Mangrove

## INTRODUCTION

Mangrove forest is one of the most important ecosystems of natural ecosystems. Mangroves have various essential functions, such as holding back sedimentation, tsunamis, and ocean waves, and other benefits for coastal and land areas. (Harefa et al., 2022) Mangrove forests can protect against erosion, abrasion, windbreakers, waves, and seawater intrusion. According to (Bachmid et al., 2018), mangrove forests have an essential function as other forest functions, namely absorbing and storing carbon stocks. (Murdiyarso et al., 2015) Suggest that Indonesia's mangrove forests store 3.14 billion tonnes of blue carbon. Mangrove forests also have other functions, namely physically as a barrier to coastal abrasion and seawater intrusion and biological processes as a habitat for various animals and aquatic biota (Raharjo et al., 2015).

Besides its many functions and benefits, mangrove forests are experiencing extensive degradation worldwide (Alongi, 2012). Currently, mangrove forests in Indonesia are 3.49 million hectares (100%) which are divided into forest areas of 2.17 million hectares (62.18%) and non-forest regions of 1.32

million hectares (37.82%) (KKP, 2021). According to (Onrizal, 2010), Indonesia's mangrove forest area is almost 50% of the Asian mangrove area and nearly 25% of the World's mangrove area. Mangrove forest is an ecosystem that dominates coastal wetlands worldwide (Kuenzer et al., 2011). As a productive coastal ecosystem, mangrove forests have complex and unique criteria because they can grow in saltwater and brackish water or river deltas (Darmawan et al., 2015).

Mangrove forests experience various threats, such as air pollution, mangrove logging, fragmentation, and rising sea surface temperatures (Giri et al., 2011). Another threat to mangrove forests is that their use is often converted because they grow in coastal areas and are adjacent to or adjacent to human activity, such as settlements, waste disposal, industrial sites, and other human activities that cause ecosystem damage (Valiela et al., 2001). Damage to mangrove forests will impact human life, and this is because mangrove forests cannot provide value for human life. (Chen et al., 2017) suggested that mangrove forests provide significant ecological, social, and economic benefits for human life. Based on data from the Ministry of Environment and Forestry (2021), Indonesia's mangrove forest area is 3,364,076 hectares. The area of mangrove forests in Indonesia is divided into three classifications, namely dense mangroves with an area of 3,121,239 hectares (93%), medium mangroves with an area of 188,363 hectares (5%), and rare mangroves with an area of 54,474 hectares (2%).

According to (FAO, 2007), mangroves on earth have decreased by 20% since 1980 and are worrying for coastal ecosystems and the environment (Wicaksono et al., 2011). This decline occurred due to various factors, both human factors and natural factors (natural disasters). (Barbier EB et al., 2011) The most significant decline in mangrove forests was caused by human actions such as coastal area development, urban development, converting mangrove land into ponds, and infrastructure development. According to (Donato et al., 2012), mangrove forests have decreased 30-50% in the last half-century due to coastal areas and excessive mangrove logging.

Reduction or degradation of the area of mangrove forests requires an action to minimize the decrease in mangrove forests, and appropriate handling is carried out, one of which is monitoring and conservation. Monitoring and protecting mangroves must be done to determine changes in mangrove forests, especially in cultivated and non-cultivated mangrove forest areas. According to (Chow, 2018), monitoring and conserving mangrove forests is a promising strategy to reduce atmospheric disturbances and help climate change, especially in coastal communities. (Suprayogi et al., 2022) Stated that one of the efforts to overcome the reduction of mangroves is to restore mangroves on a large scale and sustainably.

One way to monitor and conserve mangrove forests is by utilizing remote sensing to map mangrove forest areas. Remote sensing is the most ideal and practical method and technique for mapping the spatial distribution of mangrove forests because it combines image data and field surveys (Heumann, 2011). Remote sensing has a significant role in spatial analysis because it is fast and efficient in monitoring mangrove areas in areas difficult to reach for data acquisition to save costs and time (Kamal & Phinn, 2011).

Mangrove forest mapping has significant benefits, including knowing the characteristics of mangroves, mangrove distribution, and mangrove species and providing information on environmental changes (Dat Pham et al., 2019). According to (Kamal & Phinn, 2011), mapping of mangroves (coastal areas) is necessary to provide land inventories, assess changes in a certain period (temporal), measure biodiversity,

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and provide information for making management policies. The use of remote sensing methods and techniques for mapping mangroves has been carried out with various spatial resolutions and multi-temporal images. (Nguyen et al., 2020) Suggested that mangrove forest cover can be detected and identified using multitemporal image data.

One area in Indonesia with mangrove forests is North Luwu Regency, South Sulawesi Province. According to (Ferdian et al., 2021), based on data from the South Sulawesi Provincial Forestry Service (2019), the mangrove forest in North Luwu Regency is 16,000 Ha. The mangrove forest of North Luwu Regency was damaged by 3,840 Ha (24%) caused by the conversion of land to ponds, conversion to citrus farming land, and conversion to residential areas.

This study uses Landsat 8 imagery and Sentinel-1 imagery for 2015-2020. Landsat 8 imagery has the advantage of the spectral channel to represent objects on the earth's surface well, even though it has constraints on the influence of the atmosphere. Meanwhile, the Sentinel-1 image has advantages in data free from atmospheric effects but is limited to the spectral channel, which only has two polarizations. The difference in image data is used to exploit its advantages in analyzing mangrove forest land. According to (Wicaksono, 2017), mangrove mapping using remote sensing with different spatial and spectral resolutions is needed to address various mangrove management needs. This study compares image classification methods using multisensory data to analyze land cover changes in mangrove forests in North Luwu Regency, South Sulawesi, 2015-2020.

## RESEARCH METHODS

### Research Location

North Luwu Regency is one of the regencies included in the administration of South Sulawesi Province. North Luwu Regency has an area of 7,502.58 km2, divided into 11 sub-districts, four sub-districts, and 16 villages. Geographically, North Luwu Regency is located at 010 53' 19" - 02° 55' 36" South Latitude and 119° 47' 46" - 120° 37' 44 East Longitude. North Luwu Regency is located in the northernmost part of South Sulawesi Province (Figure 1).

Mangrove forests that grow along the North Luwu Regency's coastal areas benefit human life and the coastal environment. Based on data from the Environmental Manager of North Luwu Regency, North Sulawesi Province (2017), mangrove forests have been degraded by around 40.45% (2,433 Ha). Therefore, studying to see changes in mangrove land cover in the North Luwu Regency, South Sulawesi Province, is necessary. The mangrove forests of the North Luwu Regency do not yet have actual data regarding the area of mangrove forests and the types of mangroves found in mangrove forests. The mangrove forests of the North Luwu Regency have a good representation for research. They can be used for monitoring and conserving the area of mangrove forests.

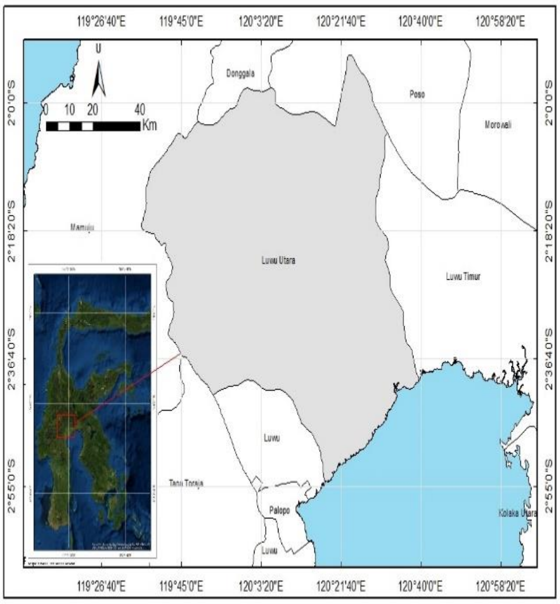

Figure 1. Research Location Map

**Research data**

Landsat 8 was launched on February 11, 2013. The Landsat 8 OLI/TIRS used is at level 1 with 11 multispectral bands with a spatial resolution of 30 m. Each band in the image has a different character and displays land cover information. This relates to the wavelength range of the recorded object's solar reflectance. For more details, the characteristics of the Landsat 8 band can be seen in fact in Table 1.

Table 1. Characteristics of Landsat 8 Image

| Band | Resolution (m) |
|---|---|
| Band 1 - Coastal aerosol | 30 |
| Band 2 - Blue | 30 |
| Band 3 - Green | 30 |
| Band 4 - Red | 30 |
| Band 5 – NIR (Near Infrared) | 30 |
| Band 6 - SWIR 1 | 30 |
| Band 7 - SWIR 2 | 30 |
| Band 8 – Panchromatic | 15 |
| Band 9 – Cirrus | 30 |
| Band 10 - Thermal Infrared | 100 |
| Band 11 - Thermal Infrared | 100 |

Source: USGS, 2021.

**Sentinel 1**

Data Sentinel-1 was launched on April 3, 2014. Sentinel-1 is at the GRDH (Ground Range Detected High Resolution) level with VH and VV polarization. Sentinel-1 uses the C-Band frequency wavelength to detect and record objects on the earth's surface that originate from electromagnetic energy. Sentinel-1 has single and dual-polarization capabilities and has the following observation modes:

1. Wave Mode: 5 Meters resolution, 20 x 20 km coverage area.
2. Extra Width Swath: 20 Meters resolution, 400 x 400 km coverage area
3. Interferometric Wide Swath: 20 meters resolution

The acquisition characteristics of the IW Sentinel-1A mode can be seen in Table 2.

Table 2. Characteristics of Sentinel Image 1

| Characteristics | Value |
|---|---|
| Swath width | 250 km |
| Incidence angle range | 29,1° - 46,0° |
| Azimuth Resolution | 20 m |
| Ground Range Resolution | 5 m |
| Azimuth and range look | Single |
| Polarization options | Dual HH+HV, VV+VH<br>Single HH, VV |
| Maximum Noise Equivalent Sigma Zero (NESZ) | -22 dB |
| Radiometric stability | 0,5 dB(3σ) |
| Radiometric accuracy | 1 dB(3σ) |
| Phase error | 5° |

Source: USGS, 2021.

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Radar is a microwave active sensor remote sensing system that can be used in almost all-weather conditions. Radar images only have two polarizations, namely VH and VV, so for interpretation, one synthetic band must be added to get the RGB band of an image. The electromagnetic waves emitted by radar are in the form of radio waves and microwaves. The reflection of the radiated waves is used to detect objects on the earth's surface (Damanik, 2018).

**Research Methods**

This study uses Sentinel-1 and Landsat 8 OLI images with a multitemporal approach for 2015-2020. The object-Based Image Analysis (OBIA) classification method considers object, structure, and shape aspects in segmenting objects on the surface. So, with 11 multispectral bands, band visualization can be done to make it easier to distinguish objects. The object-Based Image Analysis (OBIA) approach is often used to map mangrove species with higher overall accuracy results than pixel-based approaches to detect mangroves (Kamal & Phinn, 2011). Meanwhile, Radar Sentinel-1 data processing uses the Maximum Likelihood classification method based on the image pixel approach because it is limited to the polariasis band.

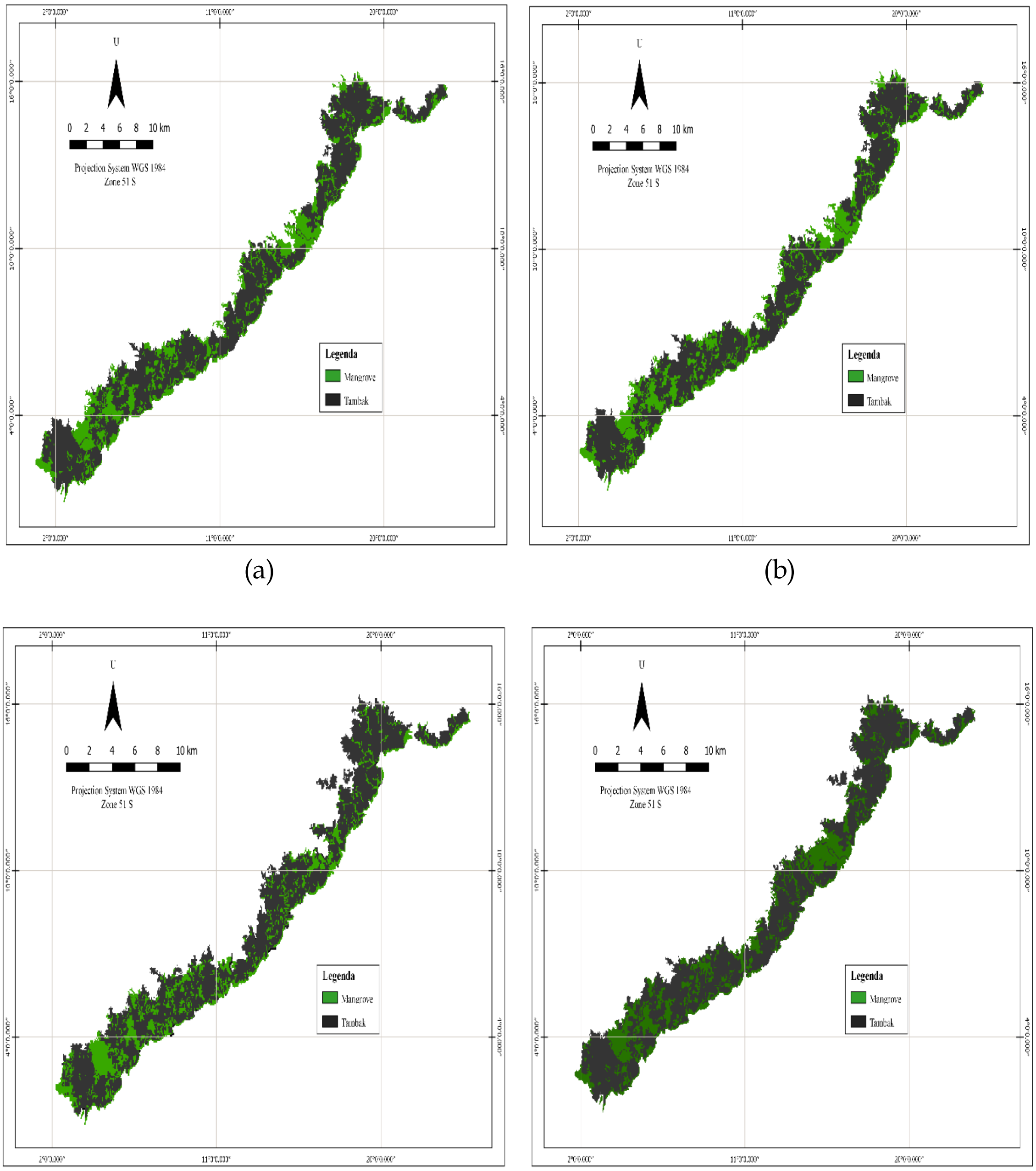
**Image Data Processing**

Sentinel-1 image data processing goes through several main stages: geometric correction, speckle filtering, terrain correction, and radiometric correction. While Landsat 8, radiometric correction is carried out to correct pixel values that do not match the reflection value or spectral emission of the actual and atmospheric object to eliminate the influence of the atmosphere on the image when recorded by the sensor. The following process is that the corrected Landsat 8 image is used as input for processing the OBIA classification process using Ecognition software. Image interpretation is carried out to determine land use classification. Meanwhile, Sentinel Image 1 uses a supervised method, namely maximum likelihood. The overall accuracy test (OA) is used to determine the accuracy of the classification technique applied to the map based on the high-resolution Google Earth satellite data.

## RESULTS AND DISCUSSION

**Landsat Image Analysis 8**

Landsat 8 is an optical sensor image with medium spatial resolution capability (30m) widely used in remote sensing needs, including land use classification. In this study, the composite band 654 was used to see differences in the appearance of objects in the study area. The OBIA-based classification using Ecognition with multi-resolution segmentation methods, namely Scale Parameter 50, Shape 0.2, and Compactness 0.5, resulted in insignificant multitemporal mangrove cover changes. The Landsat 8 image analysis results can be seen in Figure 3 and Table 3 below.




(a) (b) (c) (d)

Figure 3. (a) 2015 Mangrove Cover, (B) 2017 Mangrove Cover, (C) 2020 Mangrove Cover, (D) 2015-2020 Mangrove Cover

Table 3. Area of Mangrove Change in 2015-2020

| Land Cover | Year | | | Change | | | (%) |
|---|---|---|---|---|---|---|---|
| | 2015 | 2017 | 2020 | 2015-2017 | 2017-2020 | 2015-2020 | |
| Mangrove (Ha) | 5.235 | 5.021 | 4.639 | 214 | 382 | 596 | 3,90 |

Source: Analysis Results, 2021.

Based on Table 3, the change in mangrove forests in North Luwu Regency within five years is (-596 Ha). Ponds and non-mangrove dominate the conversion of mangrove forest land in the North Luwu Regency. Five years, the use of pond land continues to increase in the area due to the value of more profitable economic factors.

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According to (Suhendra et al. 2019), changes in mangrove forests in North Luwu Regency, besides being converted into ponds, other factors are conversion to agricultural land and mangrove exploitation by logging by local communities for living necessities. Mangrove forests in coastal areas often clash with human interests, such as port development, tourist areas, and changes in the function of ponds, thereby reducing the benefits of mangrove forests for life (Ahmad, 2019).

**Sentinel 1 SAR Image Analysis**

Sentinel-1A image processing is performed to distinguish land cover classes in the research area. The process begins with selecting samples to be classified according to the image's appearance, which is then classified using the Maximum Likelihood method. This method is commonly used and is a standard method considering various factors, including the probability of a pixel being classified into a specific class or category (Jaya et al., 2001).

The results of the interpretation of land cover classes are divided into 2, namely mangroves and ponds, using VH polarization to focus on seeing changes in mangrove land cover. This was done due to the difficulty distinguishing mangroves from other vegetation because the plants in the study area were homogeneous. According to (Damanik, 2018), SAR image data is still difficult to interpret compared to optical images because the intensity of the signal captured by the sensor is called the backscatter coefficient (s°) in decibels (dB) caused by various configurations, various polarizations, and various angles of incidence resulting in surface the same will result in different backscatter coefficients.

Visually, no specific color indicates the type of land cover, except for pond land with a surface flooded with water. It will be easier to recognize because it displays black color. Furthermore, the training area sampling uses the help of Google Earth as a reference to see differences in the image's appearance. The results of the visualization of sentinel-1 images for land cover in the study area can be seen in Figure 4 below.

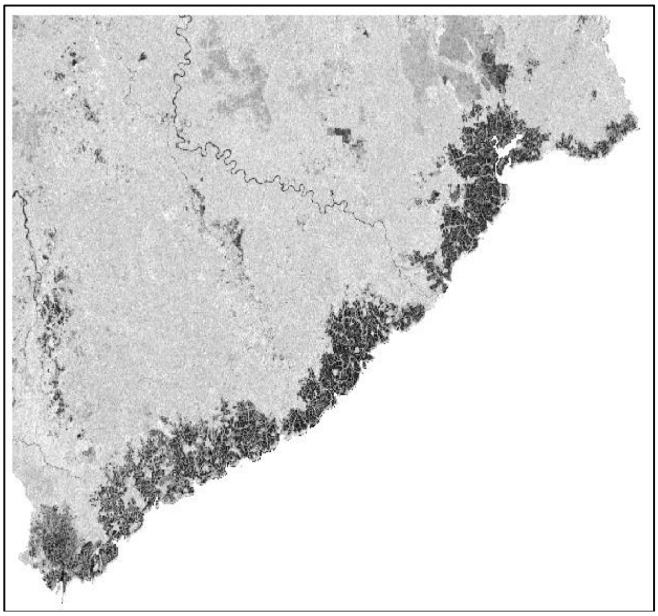

Figure 4. Visualization of the Study Area (Sentinel-1)

Based on the temporal analysis of mangrove land cover results in 2015-2020, North Luwu Regency's coastal area experienced changes that led to economic functions, such as pond areas and agricultural land. For clarity, changes in mangrove cover can be seen in Figure 5 and Table 4. From the analysis results using the texture model, the mean is the best model in classifying mangrove cover other models. Then these results are used to see changes in mangrove cover from color composites over five years.

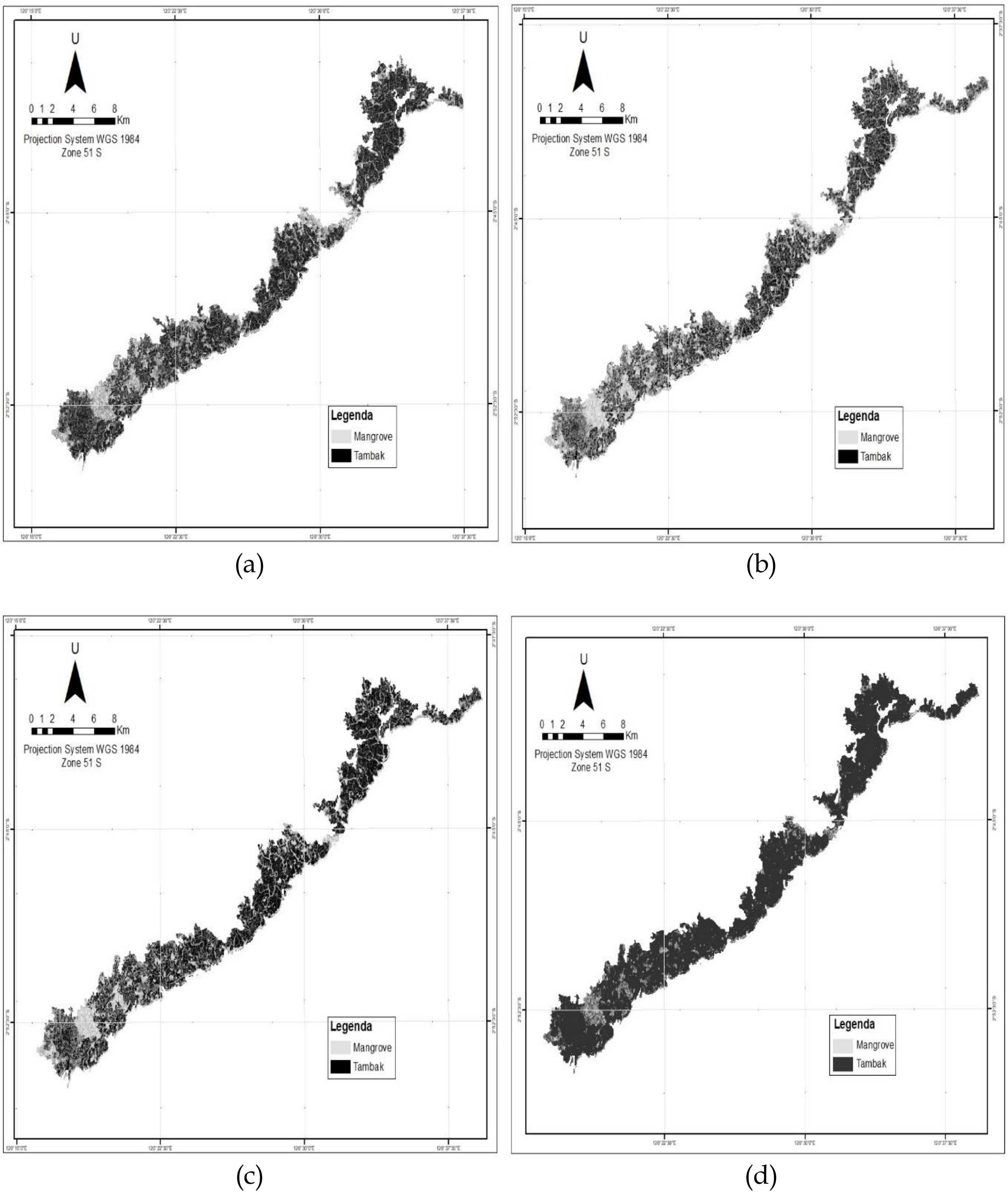


Figure 5. (a) 2015 mangrove cover, (b) 2017 mangrove cover, (c) 2020 mangrove cover, (d) 2015-2020 mangrove cover

Table 4. Area of Mangrove Change in 2015-2020

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https://doi.org/10.24114/tgeo.v11i2.41349 (Vol. 11 No. 2 – 2022)
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| Land Cover | Year | | | Change | | | (%) |
|---|---|---|---|---|---|---|---|
| | 2015 | 2017 | 2020 | 2015-2017 | 2017-2020 | 2015-2020 | |
| Mangrove (Ha) | 5.222,9 | 4.841,73 | 4.773,68 | 381,17 | 68 | 449,17 | 3,02 |

Source: Analysis Results, 2021.

Based on the data in Table 4, there was a change in mangrove land over five years (-449.17 Ha). The conversion of mangrove land is due to the higher economic value of mangroves, so it continues to occur in mangrove areas on the coast. Expanding the pond area impacts the shrinking of the mangrove forest area due to the agricultural and plantation sector businesses. Hence, it interferes with the function of the mangrove area as a place to protect coastal ecosystems (DLH North Luwu Regency, 2017).

**Comparison of Classification Results**

The results of the classification of mangrove cover changes using optical data through the OBIA approach and the category of SAR data using the Supervised Maximum Likelihood method gave different results. The difference in the results obtained using the classification method shows a change in mangrove land cover every year in the study area. The results of the analysis of Sentinel-1 and Landsat 8 images provide information on changes in mangrove land cover during 2015-2020, with an area of 449.17 Ha and 596 Ha.

This is in line with the results of land interpretation conducted by DLH Kab. North Luwu that until 2017 there had been a change in mangrove land covering an area of 2,433 Ha. Although the mangrove forest ecosystem is classified as a recoverable resource, a continuous change in mangrove land will significantly impact economic, ecological, and social functions.

Classification using the OBIA method showed better results than the maximum likelihood, although there was no significant difference in numbers. This can be attributed to OBIA considering spectral and spatial aspects in classifying. So that in conducting the analysis, we can coordinate the appearance of objects through band visualization on medium spatial resolution images such as Landsat 8 (Wibowo & Suharyadi, 2009).

While the maximum likelihood pixel-based classification method is a classification system that is currently considered the most complex and belongs to the parametric approach, which uses the assumption and requirement that each class must be normally distributed (Gaussian), however, in reality, it is pretty difficult to find courses that are usually dispersed, so the opportunity for errors in taking the training area to separate pixels from different classes is possible (Pratiwi et al., 2020). For further classification results, other research is needed to ascertain changes in mangrove land cover in North Luwu Regency.

The OA (Overall Accuracy) test with the method used for mangrove classification using OBIA and Maximum Likelihood shows a number above 80% which means the classification results are acceptable. The classification method gives good results because mangroves have unique growth characteristics only in coastal areas, so they quickly recognize the shape and growth pattern. It is easy to classify using different methods. For more details, the accuracy-test value can be seen in Table 5.

Table 5. Comparative Value of Accuracy Test

| Citra | Tahun | | | Akurasi |
|---|---|---|---|---|
| | 2015 | 2015 | 2015 | |
| Landsat 8 | 90 | 90 | 87,5 | *Overall* Akurasi *(%)* |
| | 86,66 | 86,66 | 83,33 | Koefisien Kappa *(%)* |
| Sentinel 1 | 95 | 80 | 85 | *Overall* Akurasi *(%)* |
| | 90 | 60 | 90 | Koefisien Kappa *(%)* |

Source: Analysis Results, 2021.

**CONCLUSION**

There has been a change in mangrove land cover in the coastal area of Kab. North Luwu during 2015-2020. Changes occur due to the conversion of functions into ponds, plantations, and other parts. It is necessary to act by the local government and competent parties to prevent continuous land degradation every year. The classification results using object-based methods (OBIA) and Maximum Likelihood can show good results because mangroves have unique characteristics easily identified for classification. Further research is needed to acquire the results of the study conducted.

**REFERENCE LIST**


Ahmad, A., Fisu, A. A., & Didiharyono, D. (2019). Analisis Potensi Ekosistem Mangrove Sebagai Pengembangan Objek Wisata (Studi Kasus: Kabupaten Wakatobi). Prosiding, 4(1).

Alongi, D. M. (2012). *Present state and future of the World's mangrove forests Present state and future of the World's mangrove forests*. *November 2002*. https://doi.org/10.1017/S0376892902000231

Bachmid, F., Sondak, C., & Kusen, J. (2018). Estimasi penyerapan karbon hutan mangrove Bahowo Kelurahan Tongkaina Kecamatan Bunaken. *Jurnal Pesisir Dan Laut Tropis*, *6*(1), 8. https://doi.org/10.35800/jplt.6.1.2018.19463

Barbier EB, Hacker SD, Kennedy C, Koch EW, Stier AC, & Silliman BR. (2011). The value of estuarine and coastal ecosystem services. *Ecological Monographs*, *81(2)*(2), 169–193.

Chen, B., Xiao, X., Li, X., Pan, L., Doughty, R., Ma, J., Dong, J., Qin, Y., Zhao, B., Wu, Z., Sun, R., Lan, G., Xie, G., Clinton, N., & Giri, C. (2017). A mangrove forest map of China in 2015: Analysis of time series Landsat 7/8 and Sentinel-1A imagery in Google Earth Engine cloud computing platform. *ISPRS Journal of Photogrammetry and Remote Sensing*, *131*, 104–120. https://doi.org/10.1016/j.isprsjprs.2017.07.011

Chow, J. (2018). Mangrove management for climate change adaptation and sustainable development in coastal zones. *Journal of Sustainable Forestry*, *37*(2), 139–156. https://doi.org/10.1080/10549811.2017.1339615

Damanik, Y. V. (2018). *Penggunaan Citra Radar Sentinel-1 Untuk Identifikasi Tutupan Lahan di Kabupaten Pakpak Bharat*.

Darmawan, S., Takeuchi, W., Vetrita, Y., Wikantika, K., & Sari, D. K. (2015). Impact of topography and tidal height on ALOS palsar polarimetric measurements to estimate aboveground biomass of mangrove forest in Indonesia. *Journal of Sensors*, *2015*. https://doi.org/10.1155/2015/641798

Dat Pham, T., Xia, J., Thang Ha, N., Tien Bui, D., Nhu Le, N., & Tekeuchi, W. (2019). A review of remote sensing approaches for monitoring blue carbon ecosystems: Mangroves, seagrasses and salt marshes during 2010–2018. *Sensors (Switzerland)*, *19*(8). https://doi.org/10.3390/s19081933

Donato, D. C., Kauffman, J. B., Murdiyarso, D., Kurnianto, S., Stidham, M., & Kanninen, M. (2012). Mangrove adalah salah satu hutan terkaya karbon di kawasan tropis. *CIFOR Brief*, *13*(12), 12.

Ferdian, A., Sm, S., Ilmu, J., Negara, A., Ilmu, F., & Politik, I. (2021). *Pemberdayaan Masyarakat Berbasis Modal Sosial Dalam Rangka Pelestarian Hutan Mangrove Oleh : Kerusakan Mangrove sering terjadi di daerah pesisir provinsi Sulawesi Selatan Sumber Data : Dinas Kehutanan Provinsi Sulsel 2019*. *10*(1), 54–66. http://www.ejournal.unmus.ac.id/index.php/societas/article/view/3296/1896

Giri, C., Ochieng, E., Tieszen, L. L., Zhu, Z., Singh, A., Loveland, T., Masek, J., & Duke, N. (2011). Status and distribution of mangrove forests of the world using earth observation satellite data. *Global Ecology and Biogeography*, *20*(1), 154–159. https://doi.org/10.1111/j.1466-8238.2010.00584.x

Harefa, M. S., Nasution, Z., Mulya, M. B., & Maksum, A. (2022). Mangrove species diversity and carbon stock in silvofishery ponds in Deli Serdang District, North Sumatra, Indonesia. *Biodiversitas*, *23*(2), 655–662. https://doi.org/10.13057/biodiv/d230206

Heumann, B. W. (2011). An object-based classification of mangroves using a hybrid decision tree-support vector machine approach. *Remote Sensing*, *3*(11), 2440–2460. https://doi.org/10.3390/rs3112440

Jaya, I. N. S., Saleh, M. B., Ismail, R. I., Hendri Nurwanto, Kusmana, C., & Abe, N. (2001). *Practical Technique For Detecting Mangrove Vegetation Using Digital Mos Messr and Landsat-5 TM Images: A Case Study in Karawang Cape, West Java*. *VII*(1), 23–36.

Kamal, M., & Phinn, S. (2011). Hyperspectral data for mangrove species mapping: A pixel-based and object-based approach comparison. *Remote Sensing*, *3*(10), 2222–2242. https://doi.org/10.3390/rs3102222

Kuenzer, C., Bluemel, A., Gebhardt, S., Quoc, T. V., & Dech, S. (2011). Remote sensing of mangrove ecosystems: A review. In *Remote Sensing* (Vol. 3, Issue 5). https://doi.org/10.3390/rs3050878

Murdiyarso, D., Purbopuspito, J., Kauffman, J. B., Warren, M. W., Sasmito, S. D., Donato, D. C., Manuri, S., Krisnawati, H., Taberima, S., & Kurnianto, S. (2015). The potential of Indonesian mangrove forests for global climate change mitigation. *Nature Climate Change*, *5*(12), 1089–1092. https://doi.org/10.1038/nclimate2734

Nguyen, H. H., Tran, L. T. N., Le, A. T., Nghia, N. H., Duong, L. V. K., Nguyen, H. T. T., Bohm, S., & Premnath, C. F. S. (2020). Monitoring changes in coastal mangrove extents using multi-temporal satellite data in selected communes, Hai Phong City, Vietnam. *Forest and Society*, *4*(1), 256–270. https://doi.org/10.24259/fs.v4i1.8486

Onrizal. (2010). Perubahan Tutupan Hutan Mangrove di Pantai Timur Sumatera Utara Periode 1977-2006 Onrizal. *Jurnal Biologi Indonesia*, *6*(2), 163–172.

Pratiwi, A. W., Muh, L., Jaya, G., & Saleh, F. (2020). *Perbandingan Metode Berbasis Piksel Dan Objek Citra Sentinel 2A Untuk Klasifikasi Penggunaan Lahan*. *4*(1), 117–124.

Raharjo, P., Setiady, D., & Zallesa, S. (2015). *Menjadi Lahan Tambak Di*

*Kawasan Pesisir Kabupaten Cirebon Identification Coastal Damage Due To the Mangrove Forest Conversion Into Farms Land in a Coastal Area of Cirebon District*. *13*(1), 9–24.

Suprayogi, B., Purbopuspito, J., Harefa, M. S., Panjaitan, G. Y., & Nasution, Z. (2022). Ecosystem Carbon Stocks of Restored Mangroves and Its Sequestration in Northern Sumatra Coast, Indonesia. *Universal Journal of Agricultural Research*, *10*(1), 1–19. https://doi.org/10.13189/UJAR.2022.100101

Valiela, I., Bowen, J. L., & York, J. K. (2001). *Mangrove Forests : One of the World's Threatened Major Tropical Environments*. *51*(10).

Wibowo, T. S., & Suharyadi, R. (2009). Aplikasi Object-Based Image Analysis (OBIA) untuk Deteksi Perubahan Penggunaan Lahan Menggunakan Citra ALOS AVNIR-2. *International Safeguards and Satellite Imagery: Key Features of the Nuclear Fuel Cycle and Computer-Based Analysis*, 107–111. https://doi.org/10.1007/978-3-540-79132-4_8

Wicaksono, P. (2017). Mangrove aboveground carbon stock mapping of multi-resolution passive remote-sensing systems. *International Journal of Remote Sensing*, *38*(6), 1551–1578. https://doi.org/10.1080/01431161.2017.1283072

Wicaksono, P., Danoedoro, P., Hartono, H., Nehren, U., & Ribbe, L. (2011). Preliminary work of mangrove ecosystem carbon stock mapping in small island using remote sensing: above and below ground carbon stock mapping on medium resolution satellite image. *Remote Sensing for Agriculture, Ecosystems, and Hydrology XIII*, *8174*(October 2011), 81741B. https://doi.org/10.1117/12.897926