# ANALYSIS OF MANGROVE COVER DYNAMICS IN LIANGA, SURIGAO DEL SUR USING TIME SERIES EARTH OBSERVATION DATA

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# ANALYSIS OF MANGROVE COVER DYNAMICS IN LIANGA, SURIGAO DEL SUR USING TIME SERIES EARTH OBSERVATION DATA

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**Abstract:** *Mangroves provide essential social, economic, and environmental benefits as ecosystem goods and services. In Surigao del Sur, mangrove cover declined by 24%, from 8,246 ha in 2003 to 6,281 ha in 2016. This study utilized GIS and remote sensing to map land cover changes from 2003, 2013, 2016, 2019, and 2022, and assess mangrove dynamics. From 2003 to 2013, 31.51 ha of inland water converted into mangroves, while 36.01 ha shifted to other land classes. Inland water converted 49.31 ha into mangroves by 2013 and 19.48 ha by 2016. Mangroves converted to built-up areas increased by 8.25 ha in 2019. Conversion to palm (17.03%) was higher than to barren land, seashores, or croplands. Rapid mangrove-to-built-up changes were recorded at 4.43% (2003–2013), with smaller rates afterward. Inland water changes were also consistent: 2.07% (2013–2016), 0.64% (2016–2019), and 1.23% (2019–2022).*

**Keywords:** Mangroves; Change Detection, Remote Sensing, Land-use Land Cover, Mangrove Vegetation Index

## 1. INTRODUCTION

Mangroves are a special variety of tropical forests situated at active land and water meeting point. They can thrive in saline water and are found throughout beaches and estuaries across the tropics and subtropics, prospering in circumstances to which only a few species have adapted [1]. Mangroves forest are necessary as well as its ecosystem benefits are crucial in achieving Sustainable Development Goals [2]. Mangroves also are essential in a way that the development of mangrove-based ecotourism positively impacts local communities, with success attributed to community participation, education-focused tourism, and conservation initiatives [3]. Philippine mangrove forests play intricate and highly specialized roles in tropical coastal environments. A kind of tree that has adapted to grow in tidal flats along the ocean's edge is what gives mangroves their name. Whereas other plant species would perish in the saline coastal waters, mangroves thrive there. Since 1925, more than 337 000 hectares of mangrove tracts have been lost in the Philippines due to aquaculture activities. Because polluted aquaculture replaces the function of mangroves when they are removed for aquaculture, the environmental impact is exponential [4].

Mangroves are classified by the Department of Environment and Natural Resources (DENR) as a component of the coral reefs and seagrass coastal and marine environment. The mangrove is referred to as the "rainforest of the sea," Like the upland rainforest, it supports the coastlines economically and ecologically. Alcohol, medications, tannin, lumber, and building materials can all be found in mangroves [5].

Mangrove forests are among the most critically endangered tropical ecosystems on Earth. Over 35% of the mangroves in the world have already vanished. Mangroves are disappearing at a pace of up to 50% in the twenty-first century in nations like Vietnam, the Philippines, and India. Although natural disasters pose significant risks, man-made pollution poses the greatest danger to mangroves. The threats include overfishing, wherein this global overfishing crisis facing the world's oceans also affects the ecological balance of the food chains and mangrove fish communities [6].

The main drivers of mangrove deforestation in the area were identified as conversion to aquaculture ponds and agriculture, logging for timber and fuelwood, and urbanization [7]. The 3.06-kilometer bypass and diversion coastal road project of the Department of Public Works and Highways (DPWH) in Lianga, Surigao del Sur which is scheduled to be finished by the end of 2022 [8], is being opposed by locals of the municipality because they believe it would cause the destruction of at least 30 hectares of mangrove forest [9].

Remote sensing-related technology is applicable for mapping mangroves using satellite images. As satellites has revolutionized our view of the surface of planet Earth, on land, in the atmosphere, and in the sea [10]. Applications for change detection can benefit from the data from earth observation satellites which include Landsat. Change-detection applications used measure features such as distribution, setting, and development or declination. Based on the standard satellite remote sensing data, the supervised Maximum Likelihood Classifier (MLC) application was the most reliable and efficient technique for categorizing mangroves [11]. By restoring and protecting mangrove regions, the government and private organizations are attempting to find a solution to this issue. The research shows the extent of changes and its analysis in mangrove cover in Lianga, Surigao del Sur from 2003, 2013, 2016, 2019 and year 2022. As a continuous population rises, even in coastal areas, mangrove habitats have been affected by urbanization where the loss of mangroves in Lianga, Surigao del Sur has negative implications for the ecosystem services provided by mangroves, including coastal protection, biodiversity conservation; thus, assessment of the status and changes in mangrove cover in Lianga, Surigao del Sur is needed for analysis from years 2003, 2013, 2016, 2019 and year 2022.

## 2. STUDY AREA

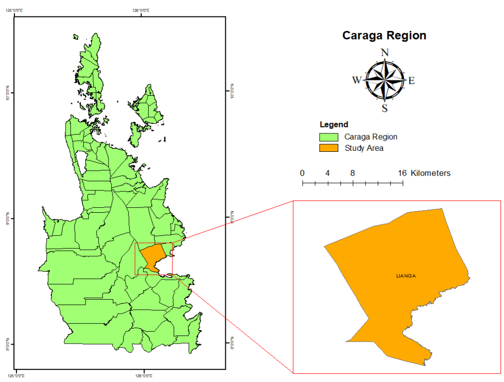


Fig. 1. Map of Study Area

The 56th Philippine province, Surigao del Sur, is situated on Mindanao's northeastern coast, facing the Pacific Ocean, between latitudes 7°55' and 9°20' north and longitudes 125°40' to 126°20' east. The estimated area of the mangrove forest in the Caraga region was 25,898 hectares, and roughly 9,072 ha was located in Surigao del Sur, according to data from the Forest Management Bureau of the DENR as of December 2010 [40].

Lianga is a coastal municipality in the province of Surigao del Sur. The municipality has a land area of 161.12 square kilometers or 62.21 square miles which constitutes 3.27% of Surigao del Sur's total area. Its population as determined by the 2020 Census was 33,869. This represented 5.27% of the total population of Surigao del Sur province, or 1.21% of the overall population of the Caraga region [42]. The study area included mangrove areas in coastal barangays of Lianga, these includes Manyayay, Diatagon, San Christine, Ganayon, Banahao, Ban-as, Poblacion, Payasan, Baucawe, and Anibongan, and Liatimco.

## 3. MATERIALS AND METHODS

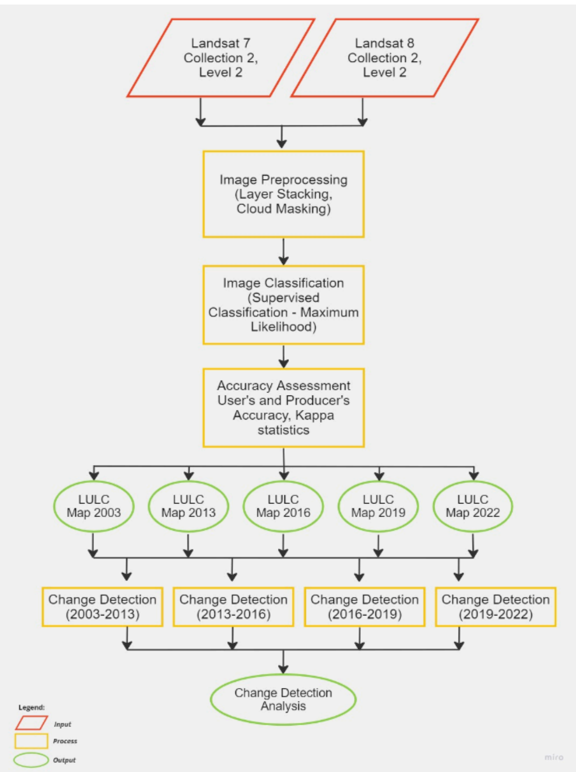


Fig. 2. Methodological Framework of the Study

### 3.1 Data Acquisition and Pre-processing

The digital satellite images are downloaded online using the website https://earthexplorer.usgs.gov/. In accessing available data sources on the archive, a polygon was created to mark the area of interest (AOI) in Lianga, Surigao del Sur, Philippines. All available high-quality satellite surface reflectance data from a series of Landsat 7 and 8 images with a spatial resolution of 30 meters were carefully selected and used to determine the changes in the mangrove habitats in the study area. The downloaded file was in a zip file, including the metadata alongside different data formats and individual bands. The downloaded Landsat 7 ETM+ C2 L2 and Landsat 8 OLI C2 L2 data are already atmospherically corrected. ENVI 5.3 and ENVI Classic are the software used for image pre-processing and processing. Summary of the downloaded datasets are summarized in Table 1.

| YEAR | DATE | SOURCE |
|---|---|---|
| 2003 | 15 – July | Landsat 7 |
| 2013 | 29 – March. | Landsat 8 |
| 2016 | 08 – June | Landsat 8 |
| 2019 | 03 – July | Landsat 8 |
| 2022 | 12 – Aug. | Landsat 8 |

Table 1. Satellite Images Dataset Summary

### 3.2 Landsat input bands

With the objective to map mangrove areas in Lianga, Surigao del Sur, this study utilized MVI's applicability. Applications for GIS and remote sensing depend on several well-established vegetation indices. Depending on what the index requires, several bands are in use. Table 2 below shows the spectral bands of Landsat 7 and Table 3 for Landsat 8, including its basic parameters. The researchers used Landsat 7's band 2, band 4, and band 5, while band 3, band 5, and band 6 for Landsat 8, respectively, all in 30m spatial resolution, following the formula.

Table 2. Landsat 7 ETM+ Spectral Bands Metadata

| Band Number | Band Name | Wavelength (micrometers) | Resolution (meters) |
|---|---|---|---|
| 1 | Blue | 0.45-0.52 | 30 |
| 2 | Green | 0.52-0.60. | 30 |
| 3 | Red | 0.63-0.69 | 30 |
| 4 | Near Infrared (NIR) | 0.77-0.90 | 30 |
| 5 | Shortwave Infrared (SWIR) 1 | 1.55-1.75. | 30 |
| 6 | Thermal | 10.40-12.50 | 60 (30) |
| 7 | Shortwave Infrared | 2.09-2.35 | 30 |

| | | | |
|---|---|---|---|
| | (SWIR) 2 | | |
| 8 | Panchromatic | 0.52-0.90 | 15 |

Table 3. Landsat 8 OLI Spectral Bands Metadata

| Band Number | Band Name | Wavelength (micrometers) | Resolution (meters) |
|---|---|---|---|
| 1 | Coastal aerosol | 0.43-0.45 | 30 |
| 2 | Blue | 0.45-0.51. | 30 |
| 3 | Green | 0.53-0.59 | 30 |
| 4 | Red | 0.64-0.67 | 30 |
| 5 | Near Infrared (NIR) | 0.85-0.88 | 30 |
| 6 | Shortwave Infrared (SWIR) 1 | 1.57-1.65 | 30 |
| 7 | Shortwave Infrared (SWIR) 2 | 2.11-2.29 | 30 |
| 8 | Panchromatic | 0.50-0.68 | 15 |
| 9 | Cirrus | 1.36-1.38 | 30 |
| 10 | Thermal Infrared (TIRS) 1 | 10.6-11.19 | 100 |
| 11 | Thermal Infrared (TIRS) 2 | 11.50-12.51 | 100 |

**3.3 Band Composite and Band Math**

The band 1, 2, 3, 4, 5, 6, and 7 were compiled to visually identify the different land cover classes, in 30 m pixel size in ENVI 5.3 software. Using the Layer Stacking Tool, these bands were loaded into the software and stacked. The MVI formula was loaded to the Band Math, bands for near infrared, green, and shortwave infrared 1, all in 30 m pixel size were utilized to generate the MVI image and used to compile with the first layer stacked image. The following is the formula of the Mangrove Vegetation Index (MVI) for Landsat 7:

$$MVI = \frac{B4-B2}{B5-B2}$$

Where:

NIR = Band 4 reflectance values
Green = Band 2 reflectance values
SWIR1 = Band 5 reflectance values

While the formula of the Mangrove Vegetation Index (MVI) for Landsat 7:

$$MVI = \frac{B5-B3}{B6-B3}$$

Where:

NIR = Band 5 reflectance values
Green = Band 3 reflectance values
SWIR1 = Band 6 reflectance values

**3.4 Cloud Masking and Buffer Zone**

One of the significant challenges in extracting information using remote sensing is that some part of the images used in this study is covered with cloud, shadow and haze, therefore covering the information in that part of the image. Using the raster calculator tool, cloud masking was then performed to all the layer stacked images, the masked cloud areas were filled in with clear view surfaces from other images. A Buffer Zone with a distance of 7.0*10^4 m in the coastal areas of the barangay was generated to ensure that mangroves offshore are included.

**3.5 Land Use/Land Cover**

The researchers covered 11 different classes which are shown in Table 4 for LULC classification. For each study period, the Region of Interest (ROI) tool was utilized to select the training samples, the maximum likelihood classification was performed using carefully selected training areas in the satellite images. For mangroves, in order to establish distinct region training among the classes, a composite will provide a color hue that contrasts between the area's coverings. In accordance with how LULC changes in the study areas, the researchers seek to illustrate the most significant changes within a relative time frame.

Table 4. Land Cover Classes and Class Definition

| Classification | Class Definition |
|---|---|
| Built-up | Residential, commercial, industrial areas, roads and bridges, and all impervious surfaces. |
| Forest | Includes trees that can be seen in built-up areas, along the roads, parks, recreational areas and trees mixed with shrubs. This class also includes sparse vegetation. |
| Cropland | Cereals, grasses, and crops not at tree height that have been planted or plotted by humans include corn, wheat, soy, and fallow areas of structured land. |
| Grassland | Natural meadows and fields with little to no tree cover, open savanna with few to no trees, parks/golf courses/lawns, and pastures. Open areas covered in homogenous grasses with little to no taller vegetation; wild cereals and grasses without visible human plotting |
| Palm | Tract of land containing coconut trees, oil palm, sago, or nipa. |
| Water | Examples of areas having year-round water include rivers, ponds, lakes, oceans, and flooded salt plains. These areas may not include areas with |

| | |
|---|---|
| | intermittent or ephemeral water, little to no sparse vegetation, no rock outcrops, and no built-up features like docks. |
| Seashore | Includes exposed river beds(sand, rocks, etc.) and sea shores |
| Mangroves | Trees and shrubs that are resilient to saltwater that flourish in protected marine intertidal zones in the tropics and subtropics |
| Barren | Denuded areas, bare soils, bare soils with thin grasses (bare soils is more dominant than grasses), and unpaved roads |
| Inland Water | Freshwater, lakes, pools, wetlands, and fishponds |

### 3.6 Accuracy Assessment

Accuracy ROIs are collected by identifying different land cover classes from Google Earth Pro. The Confusion Matrix was generated using the user and producer values and their class frequency. The user's accuracy was discussed in relation to the validity of the classes in the classified images. The percentage of properly identified pixels relative to all pixels in that ground truth class was the producer's accuracy. The user's, producer's, and general accuracy of this work, as well as the error matrix was used to generate the kappa statistics. The points are then exported as KMZ file which in the latter were loaded and validated in the ArcMap software. The calculations for the accuracy assessment were done following the equation shown below.

User's Accuracy:

$$\frac{Total\ Correctly\ Classified\ Pixel\ (each\ Category)}{(Total\ \#\ of\ referenced\ pixel\ (row)} \text{ x } 100$$

Producer's Accuracy:

$$\frac{Total\ Correctly\ Classified\ Pixel\ (each\ Category)}{(Total\ \#\ of\ referenced\ pixel\ (row)} \text{ x } 100$$

User's Accuracy:

$$\frac{Total\ \#\ Correctly\ Classified\ Pixel}{(Total\ \#\ of\ referenced\ pixel} \text{ x } 100$$

### 3.7 Change Detection

The change in mangrove from the five different classified images was identified using the post-classification change detection technique. The process was done at two different intervals, the change that occurred during 2003-2013, 2013-2016, 2016-2019, and finally from 2019 to 2022.

## 4. RESULTS

**4.1** Land Cover

The following maps are the generated land cover maps of years 2003, 2013, 2016, 2019, and 2022.

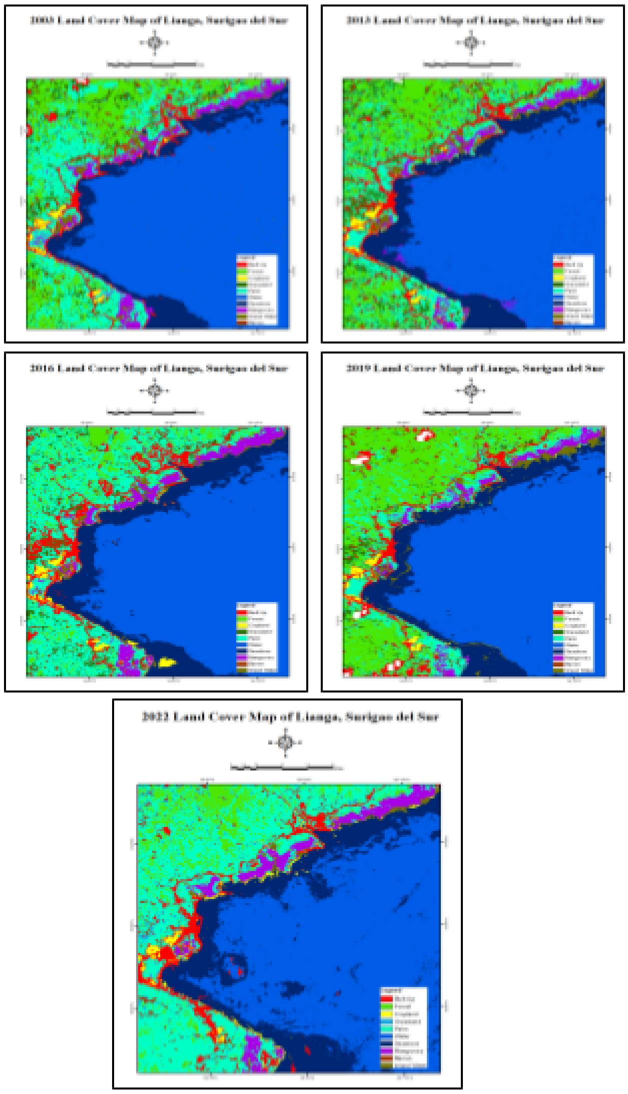

Fig. 3. Generated Land-use/Land Cover Maps

Table 5. Area of Mangroves

### 4.2 Accuracy Assessment

Training ROIs were created and processed in ENVI Classic software to generate results for the Maximum Likelihood Classification. 100 points for Accuracy ROIs were also created and used in Confusion Matrix Parameters to generate the report showing the overall accuracy, kappa coefficient, confusion matrix, errors of commission (percentage of extra pixels in class), errors of omission (percentage of pixels left out of class), producer accuracy, and user accuracy for each class.

Table 6. Average Accuracy

| Land Class | Average Accuracy (%) | |
|---|---|---|
| | User's Accuracy (%) | Producer's Accuracy (%) |
| Barren | 88.05 | 97.40 |
| Built Up | 79.29 | 88.40 |
| Forest | 91.74 | 90.80 |

| | | |
|---|---|---|
| Cropland | 96.67 | 80.80 |
| Grassland | 88.94 | 91.60 |
| Palm | 76.92 | 67.60 |
| Water | 94.43 | 95.20 |
| Seashore | 88.00 | 94.00 |
| Mangroves | 89.42 | 89.80 |

Table 6 shows the average of each land class from both User and Producer Accuracy calculated from the values acquired on 2003, 2013, 2016, 2019, and 2022. The highest average calculated was from the Cropland land class for the User's Accuracy, whereas the Barren land class got the highest average of the Producer's Accuracy during the said timeframe.

Table 7. Summary of Overall Accuracy and Kappa Coefficient

| **Year** | **Overall Accuracy** | **Kappa Coefficient** |
|---|---|---|
| 2003 | 88.10% | 0.8678 |
| 2013 | 89.50% | 0.8833 |
| 2016 | 88.80% | 0.8756 |
| 2019 | 87.60% | 0.8622 |
| 2022 | 88.10% | 0.8678 |
| | *Average*: 88.42% | |

Table 7 shows the overall accuracy and kappa coefficient from the classified map generated during maximum likelihood classification of each year. For the Overall Accuracy, results from the year 2013 garnered the highest rate of accuracy and 89.50% and the lowest rate was from the year 2019 with 87.60%. The Kappa Coefficient in 2013 also got the biggest value.

**4.3 Change Detection Analysis**

ArcMap software was used for Change Detection Analysis to perform calculations on a land class from Year 1 that changed into another land class in Year 2. The land class changes were derived using the Field Calculator in the attribute table and calculating geometry would derive the area of changes.

Table 8. Summary of Mangrove Changes Between Two-Year Comparisons in Percentage

Fig. 4. Graphical Illustration of Mangrove Changes Between Two-Year Comparison

The results of monitoring mangrove changes in four periods: 2003–2013 with a time-span of 10 years, and 2013–2016, 2016–2019, and 2019–2013 with a three-year interval are shown in Figure 22 and their statistics are shown in Table 16. Evidence from this table clearly shows that the conversion of mangrove to palm from 2003 to 2013 is 17.03% which is sharply higher than barren, seashore, cropland and other land classes with 7.51%, 4.93%, and 2.15% of change, respectively. These changes were non-significant in the context of errors associated with classification and the dynamic nature of mangrove ecosystems. These changes were well within the error margin. For example, selected areas in forest and palm trees, barren land, and water bodies could easily be misclassified from one class to another.

Hence, the changes of mangroves to built-up can be emphasized during a ten-year period since there is rapid change of 4.43%, with 0.92% from 2013 to 2016,

| Mangrove Changes | | | | |
|---|---|---|---|---|
| Land Class | (2003-2013) | (2013-2016) | (2016-2019) | (2019-2022) |
| Built Up | 4.43% | 0.92% | 0.60% | 0.63% |
| Forest | 1.81% | 0.34% | 1.72% | 0.39% |
| Cropland | 2.15% | 0.34% | 0.03% | 1.00% |
| Grassland | 0.24% | 0.18% | 0.06% | 0.02% |
| Palm | 17.03% | 0.60% | 0.16% | 2.35% |
| Water | 0.54% | 3.69% | 0.01 % | 0.00% |
| Seashore | 4.93% | 9.05% | 8.91% | 0.65% |
| Barren | 7.51% | 0.04% | 0.09% | 0.00% |
| Inland Water | 0.20% | 2.07% | 0.64% | 1.23% |

0.60% from 2016 to 2019, and 0.63% from 2019 to 2022 where human activities, such as agricultural development and road construction, have adversely affected mangroves in the coastal barangays of Lianga. From 2013 to 2016, 2016 to 2019, and 2019 to 2022, inland water has shown consistent changes with 2.07%, 0.64%, and 1.23%, respectively. As Lianga is one of the municipalities with established fish sanctuaries by the Provincial Fisheries and Aquatic Resources Office

Table 9. Summary of Mangrove - Mangrove Changes

| | Mangrove-Mangrove (%) |
|---|---|
| 2003-2013 | 61.14% |
| 2013-2016 | 82.77% |
| 2016-2019 | 87.78% |
| 2019-2022 | 93.75% |

**5. Conclusion and Recommendations**

Since remote sensing techniques demand a systematic approach to data collection, are easy to use, inexpensive, have a high degree of precision, and have the capacity to provide time series data, they are ideal for monitoring changes in the coastal environment. Since change detection is an efficient technique for visualizing, quantifying, and interpreting the patterns in mangrove ecosystems, many researchers from across the world have adopted the practice of monitoring mangrove change.

The researchers were able to produce five periods of land cover maps in Lianga, Surigao del Sur where there is a drastic change with 514.35 ha mangrove areas left in 2019 from 794.07 ha of mangrove covered area in 2016. With an overall accuracy of 88.10% in 2003, and a Kappa coefficient of 0.87, as well as 89.50% and 0.88 in 2013, 88.80% and 0.88 in 2006, 87.60% and 0.86 in 2019, and 88.10% and 0.88 in 2022, respectively. The classification findings showed a satisfactory agreement with the ground reference data. However, it still prompted misclassification; often misclassified mangrove pixels include wetlands, neighboring croplands, Nipa Palm and Coconut trees, inland vegetation, built-up, and water.

Change detection analysis was done to assess mangrove dynamics in the said study area. There has been changes that converted the mangrove forests in Lianga and were classified as other land uses which some were in areas with Inland Water. In 2003, some areas with Inland Water converted 31.51 ha of mangroves into Mangroves by 2013, while 36.01 ha of it was converted into built-up land classes. This was due to aquaculture, where some mangrove forests were cleared out and converted into fishponds of landowners. Since 2013, some areas with Inland Water have converted 49.31 ha into Mangroves by 2016, while abandoned ponds have made mangrove forests grow more and scatter. From 2016, some areas with Inland Water have converted 19.48 ha into Mangroves by 2019, while mangroves converted to built-ups also increased with 8.25 ha compared to the area changed in 2013-2019. As for 2019, some areas with Inland Water have converted 39.07 ha into Mangroves by 2022.

The conversion of mangrove to palm from 2003 to 2013 is 17.03%, which is higher than barren, seashore, cropland, and other land classes. A rapid change of 4.43% from 2003 to 2013 of mangroves to built-up, with 0.92% from 2013 to 2016, 0.60% from 2016 to 2019, and 0.63% from 2019 to 2022. And from 2013 to 2016, 2016 to 2019, and 2019 to 2022, inland water has shown consistent changes with 2.07%, 0.64%, and 1.23%, respectively.

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